Dynamic Rust Code-Generator

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Abstract

Sammanfattning

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Chapter 1

Introduction

Modern software development in the Big Data domain focus on scale-out performance. Instead of improving the capacity of a single computer, called scale-up, the program will run on a large set of possibly distributed machines. Coordination in such a parallel distributed setting is non-trivial and error prone. Therefore, most developers turn to abstract high-level framework for parallel programming where the distribution is implemented implicitly by the framework [1] [4]. This will enable developers with limited experience of distributed parallel execution and coordination to still take advantage of the performance gain of the scale-out paradigm [7]. Most of the state-of-art distributed frameworks run on the Java Virtual Machine (JVM) [4] **Citat till Spark**. This will work fine on a homogeneous cluster but it will be inefficient on a heterogeneous cluster. A heterogeneous cluster contains different types of hardware accelerators combined with general central processing units (CPUs), such as graphics processing unit (GPU) and field-programmable gate array (FPGA).

To fully utilise the potential of such a cluster, the code would need to be specifically tailored for the underlying hardware of each individual node. This is a continuous problem since vendors of accelerators tend to update and release new application programming interfaces (APIs) to enable more efficient use of their hardware. If an application explicitly use the API it would not be portable. Making sure that an application continues to be portable to new hardware and APIs would require substantial continuous manual efforts by the application developer. Using a more high-level framework for distributed parallel computing, the responsibility of continuous portability maintenance

is shifted to the developer of the framework. Thus, the application developer will be alleviated of this strenuous work effort [6].

Deep Neural Networks (DNNs) is a machine learning technique depending on effective computations of floating point operations. GPUs are usually used for executing DNNs due to their superior parallel computing power. An architecture which has an emerging potential for substituting and complementing GPUs are FPGAs. The main advantage of FPGAs is their energy efficiency. [16] compare the performance and energy efficiency of future FPGAs compared to current state-of-art GPUs. The FPGAs were able to perform 10% to 50% better than the GPUs whilst requiring about half the energy consumption per operation. This shows that the components in a state-of-art heterogeneous cluster can change in the future.

1.1 Background

Spark is an expressive framework for distributed parallel computing running on the JVM. Spark aims to improved performance by avoiding moving data eagerly to external stable storage. Other popular distributed computing frameworks prior to Spark moved all intermediate result to an external stable storage, such as a distributed database, to guarantee fault tolerance. This impedes their execution and decrease performance significantly. Spark introduced Resilient Distributed Datasets (RDDs) as an alternative. RDDs represent an abstract execution plans of operation on data stored in stable storage. RDDs are lazily evaluated. No intermediate results are calculated before a result from the expression the RDD represents is explicitly requested by the user. At the time when the result value is requested, Spark will optimise the execution plan and distribute the workload over the cluster. Spark improved performance of distributed parallel computing significantly, up to 20x compared to Hadoop [22].

1.1.1 Spark and Native Code Generation

Application analysing Big Data tend to utilise a mixture of procedural algorithms and relational queries. Using Sparks RDDs or other distributed computing frameworks, as Hadoop, for relational queries can be tedious and complex. It requires a lot of manual optimisation to match the performance of frameworks specialise for relational queries.

To tackle this problem, Spark introduced the DataFrame concept along with an optimiser specifically developed for query optimisation called Catalyst. DataFrames represents a distributed set of rows with a uniform schema such as a table in a relational database. These rows can be manipulated using the DataFrame API, which consists of a set of lazily evaluated relational operators. These relational operators correspond to queries in the Structured Query Language (SQL). A DataFrame can be transformed to an RDD of row objects. This bridge the gap between relational queries and procedural algorithms [1].

Sparks performance can suffer radically due to the intent to be expressive whilst keeping the distribution "under the hood". Flare is an attempt to fix a part of the performance issue, focusing on DataFrames. Spark operations on a DataFrame will originally be executed on the JVM. Running operations on a virtual machine (VM) is inherently slower than native-code. Therefore, Flare transforms relational operators on DataFrames to native code. This improved performance significantly. Sparks query performance with Flare matched the performance of the best SQL engines without affecting Sparks expansive expressiveness [8]. Flare is a showcase of the potential of moving from interpreting instructions by a VM to compiling to native code.

1.1.2 Flink, a Stream Processing Framework

Flink [4] is an open source system focused on continuous distributed computing. A Flink program will be compiled and scheduled once and then run for a long period of time. Therefore, Flink needs to be adaptive and fault tolerant during run time. To achieve this, Flink employs a dynamic cluster architecture which is composed of three processes: the client, the Job Manager and the Task Managers [5]. The client will compile and optimise the logical pipeline before sending it to the Job Manager. The Job Manager is responsible for coordination, physical deployment and fault tolerance. The Task Managers are workers, using a single JVM to execute tasks assigned to it. The system can even handle Job Manger failures using leader election in ZooKeeper [11].

1.1.3 Meta-Programming and Code Generation

Both Spark and Flink are examples of frameworks which enable the developer to focus on higher-level logical meanings of a program, high-level semantics, without requiring detailed knowledge of the underlying low-level concrete implementations. This is a form of Meta-Programming, where low-level implementations will be generated based on a higher-level abstract specification supplied by the user [19].

The problem solved by meta-programming shares some commonality with General-Purpose Languages (GPLs). A GPL supply the developer with a abstract human-readable language which the compiler in turn converts to a representation which can be interpreted by the underlying hardware. Examples of GPLs are C, C++ and Java.

Meta-programming languages is a broad category and spans over a large variety of language techniques. It can be incorporated into a GPL, using macros, templates, or data-structures to represent the intended program. Alternatively, a narrow language can be developed for the specific application domain. This is call a Domain Specific Language (DSL) [19].

Domain Specific Languages for High Performance Stream Processing

Ziria is an example of a DSL. The implementation of wireless protocols is complex due to the high throughput demands. Data in the rate of Gigabits/second have to be processed by a wireless router. Most protocols have therefore been implemented without much hardware abstractions. This enhances performance, since the programs are tailor-made for the underlying hardware, but it makes the software development process more complex and error prone. Ziria enhances the development and maintenance of wireless protocols by exposing high-level abstraction to the user. The abstraction consists of two main components: stream transformer and stream computer. A stream pipeline is built using these two components. Ziria aims to not restrict the domain experts expressiveness. To enhance performance, Ziria apply aggressive domain specific optimisation to the program and then compile it to highly optimised hardware specific native code. Ziria is an external DSL which means that the developers implemented a compiler, parser and similar tools specifically for Ziria. Implementing these tools requires a substantial effort. Instead a DSL can be embedded into a host

language to reduce the work effort by reusing the tools implemented for the host languages [10].

Lime Java [2] is another implemented DSL for stream processing on a heterogeneous cluster. Lime Java is integrated into Java and has a set of language constructs which limits the usage of global fields and static fields. It also encourages the usage of none mutable types. The constructs which enable these restrictions on methods are two keywords, local and global. A local method can only invoke other local methods while global methods may invoke either local or global methods. The local methods have the restriction that they may only access the instance's local fields, but can be part of a stateful instance. The local method can use the instance's local fields though Java's "this" construct, with the restriction that it is not a static field. The two constructs enables Lime to represent a stream pipeline into a set of autonomous tasks, where each task is a set of local methods. Hence, these tasks are guaranteed to not be in need of any synchronisation. The tasks can therefore be dynamically allocated to hardware components in the cluster. No distributed coordination aside from input-output pipelining need to be enforced between these tasks. To further decrease network traffic, connected tasks in the pipeline can be merged and assigned to a single node in the cluster. This also enables the compiler to distribute the workload efficiently and more evenly over the cluster. A running graph may be dynamically extended with new task. Added task will automatically be connected and started.

1.1.4 Continuous Deep Analytics

Continuous Deep Analytics(CDA) is a project which aims to tackle the need for computationally heavy analysis, such as DNNs in machine learning, of data-streams. Therefore, CDA needs to be able to fully utilise the computational capabilities of a heterogeneous cluster. However, this should not be done at the expense of requiring manual low-level implementation of the user. CDA will follow Spark and Flink's concept of supplying high-level abstraction to the user and implicitly handling the parallelization and distribution of the work effort.

CDA is in the starting phase so few concrete definitions of the system have been made. The initial prototype is similar to Flink, it is composed of a Client, Driver, and Worker. The Driver corresponds to Flink's Job Manager, and is responsible for splitting and distributing

the work effort as well as monitoring the cluster. The tasks will have to be compiled to native code for the workers to fully utilise the underlying heterogeneous cluster. This will also be part of the Drivers responsibility. The workers will be responsible for executing the tasks.

The Client is a front-end for the user. Implementation for the front end will be available in several programming languages. The user will specify the stream processing application in the front-end. The application will then be compiled to an intermediate representation (IR) which will then be sent to the Driver. The Driver is the responsible for splitting the application into tasks, mapping the tasks to specific workers in the cluster, and interpret the IR of each task to hardware specific native code for the workers responsible for execute the task.

1.2 Problem

CDA aims to move from Java and the JVM to increase performance. The problem with shifting to a high-performance programming languages which is compiled to native code is the loss of many safety guarantees. This has been known as the holy-grail of programming language domain, a language can either supply low-level control to increase performance, or statically guarantee run-time safety of a compiled program. Rust is a new programming language which claims to achieve both sides of this problem [12]. Therefore, CDA want to be able to generate Rust programs from the IR. The problem with Rust is that it is still not in a stable state. Rust retains the ability to do breaking updates by declaring it to be in a unstable state. Breaking updates are updates which may not guarantee backwards compatibility of new versions. Programs written in an older version of Rust may be invalidated by a later release of Rust. Also, the IR in CDA is not defined and is guaranteed to vary and expand from the prototype IR used during this thesis.

The research question is therefore: how can an interpreter of the IR to Rust be implemented to easily adapt to future changes of both Rust and the IR?

1.3 Purpose

1.4 Goal

1.4.1 Benefits, Ethics and Sustainability

1.5 Related Work

1.6 Delimitations

1.7 Outline

Chapter 2

Theoretic Background

2.1 Domain Specific Languages

GPLs are great tools for programmers who's work spans over several application domains. But a GPL might impede the development process for user which has limited experience with software development and who are specialised in a specific application domain. A more precise and narrow language may prove beneficial for such developers. Such languages are called DSLs. A good DSL should make the development process fast and efficient whilst still being correct and not limit the expressiveness within the application domain.

To develop such a DSL can become costly if it is done from scratch. To avoid this, embedded DSL takes advantage of the host language, the language the DSL interpreter is developed in. Much of the host language's syntax, semantics, development tools, and other related artefacts is reused by the DSL.

Focus during the development of the DSL can instead be shifted from syntax to the semantics of the domain specific parts of the DSL. This will reduce development cost of the DSL significantly and make it less error prone. The semantics of the DSL should be clear and capture the intuition behind the domain concepts to simplify the formal process of proving the correctness of a program [10].

2.1.1 Different embedded DSLs

Embedding of DSL is widely split into two categories, shallow and deep embedding. Shallow embedding is done by interpreting the DSL

constructs as constructs directly in the target language. Even though interpreting instruction directly to target code incurs little performance overhead, the lack of ability for domain specific optimisation in a shallow DSL can mitigate performance gain by eagerly evaluating the DSL constructs. [13] showed that, by not eagerly evaluating an domain specific language, R in that case, performance can be significantly improved. By interpreting R code as an abstract syntax tree (AST), domain specific optimisation's may be applied more effectively. Thus, performance of their non-eager interpretation of a R program in Java could outperform the regular R interpreter which was implemented in C.

Shallow embedded DSLs require a partial-evaluator to apply domain specific optimisation's to the generated code. Implementation of a partial-evaluator requires a substantial effort.

Deep embedding circumvent this problem concerning domain specific optimisation by not eagerly evaluating the DSL constructs. Instead, the DSL constructs is transformed into an IR. The IR is implemented as a data-structure and domain specific optimisation's can be applied directly do it. The resulting, optimised IR is then interpreted to corresponding constructs in the target language [9].

2.2 Multi-Stage Programming Languages

Program generators is another effective way of enhancing domain specific application development. They enable high-level abstractions which can be used to argue the semantics of the program. It should, similarly to embedded DSLs, enable these abstractions without incurring any run-time overhead due to interpretation. In contrast with embedded DSLs, instead of interpreting constructs directly in the host language, multi-stage programming language [21] use the host language as a meta code-generator and exposes staged representations to the user. The host language code express how to create a representation of the program similar to an AST. This gives a more transparent construction of the staged program and the user will easily understand what actual representation is going to be created.

Embedded DSLs interpret host language constructs to a staged representation to avoid exposing the staged representation to the user. The main reason for this is that exposing the staged representation to

the DSL user gives the user a feeling of writing a program generator instead of an actual program. The drawback of embedded DSL is that the user may find it hard to understand what the staged representation of the program will actually look like. Thus, it can be unclear what target code will be emitted for the program.

The staged AST representation enables validity checks of the semantics to verify it's correctness, as type-checking the AST. The AST can be optimised using domain specific knowledge. Source code in the target language is generated from the AST representation by the generator.

The execution of a program in a multi-staged programming language is composed of three stages; generation, compilation and execution. In comparison, execution of programs in embedded DSLs and GPLs are composed of two stages; compile-time and run-time.

The generation stage will interpret the staged programming language constructs, create the staged representation, and emit source code in the target language. The target source code is passed to the target language's compiler and compiled, e.g. to a binary executable. Lastly, the binary is executed. This is done dynamically, which means that the staged representation will be dynamically created based on the input to the program. This will enable the staged program to adapt more to the input data at the expense of dynamical staging and compilation of the actual binary. This will incur significant overhead costs during run-time if the format of the input data is inconsistent and changes a lot.

2.2.1 Lightweight Modular Staging

The program generator can be reduced to a library in the host language if it is possible to represent the expressions of the application domain as staged data-structures. This technique is called lightweight modular staging (LMS) [17]. LMS interprets domain specific constructs as data-structures. The evaluation of the expression is postponed when using staging.

Based on the staged representation of the code, domain specific optimisation's may be applied. The optimisation techniques are defined by implementing a recursive optimise method for all staged data-structure types. To generate code each staged data-structure type has to implement a compile method. Compile will recursively be called for

all staged data-structures and generate code in the target language. When using multi-methods for optimisation there are three main problems which the developer of the multi-stage programming language has to look out for: “separate type-checking/compilation, ensure non-ambiguity, and ensuring exhaustiveness”.

2.2.2 Language Virtualization Using the Stage Programming Model

Using a library of a staged programming language can be complicated. Finding the classes representing staged operations can require reading through the library implementation. A technique for alleviating the user of this and making the library more user-friendly is Language Virtualization [6].

In a virtualized staged programming language, the operations available for a specific data-type is implemented as methods for the staged representation of the data-type. The methods will however not be evaluated directly, as would be expected by regular methods. Instead the methods return a lifted, i.e. staged, representation of the operation. This lifted representation is apt for domain specific optimisation. However, from the library users perspective this will not be clearly noticeable. The lifting into a staged representation and all optimisation are done implicit by the library. This is similar to what Spark’s RDDs does, creating a execution plan which is stalled until the result is explicitly requested by the user. Using a language which supports overloading of language operators, such as "+", the virtualization and lifting can be made to include such language constructs. Thus, A + B can be lifted to Add(A, B). Scala is a language which support this kind of overloading [6].

[18] demonstrate a virtualized staged programming language embedded in Java as a library. The programs written using the library are staged implicitly. Data types in the staged programming language are represented as classes in Java. Operation on these data types are implemented as methods in the classes which return a new staged representation. The staged representation will be materialised directly as some operation is applied which is not part of the library.

2.3 The Expression Problem

The negative aspect of deep embedding of DSL and staged representation is that adding a new language construct will be hard. The new construct's interpretation has to be added to each of the interpreters. Two examples of interpretation are evaluation of an data-structure representing a program written in the DSL and comparison of two DSL programs if they are equal. If a new construct is added to the deep embedded DSL, each interpretation has to be extended to handle the new language construct.

This is weighted against shallow embedding's negative aspect that creating a new interpretation requires a complete re-implementation of the interpreter for all language constructs. Thus, extending the language interpretation requires a lot of work in a shallow embedded DSL. The problem of weighing this two aspect, effective and modular extensibility of language constructs or of interpretations, is called the expression problem [20].

[23] propose two solutions for the expression problem when using deep embedded DSLs. One solution based on object-oriented decomposition which enables easy extension of data-structures in the DSL. Each interpretation of the DSLs data-structure is composed as a function in an interface. All language constructs has to implement the interface and define the interpretation of each function based on the semantic meaning of the data-structure. Therefore, it is easy and modular to add new language constructs to the DSL. Introducing new interpretations means that the interface will be extended with functions, which in turn will require extension of all classes implementing the interface. This means that all language constructs in the DSL has to be extended to implement the new function. The second is a functional decomposition, which favours extension of interpretations. Each interpretation is implemented as a trait in Scala. The trait implement the interpretation for each language construct.

2.4 Rust Programming Language

The trade-off between giving the programmer low level control and being able to guarantee safety properties of the program is a usual problem for general purpose languages. No language has been able

to achieve both. It has been a prioritised problem in the programming language research domain [12].

Rust, developed at Mozilla Research, claim to have solved the problem without incurring overhead penalties during run-time [15]. Rust follow C++ and gives zero-cost high-level abstraction. One of Rust main concept to ensure safety properties and avoiding data-races is ownership of resources. Variables can be owned by a restricted set of pointers and special rules are employed for accessing the data. Only one pointer can have the right to modify the data at each time. Several pointer can be granted read access, but not simultaneously as one pointer have writing access.

The ownership concept along with other Rust rules severely restricts the developer. Therefore, Rust had to include a construct for unsafe scopes. In an unsafe scope, Rust will allow actions deemed unsafe by the regular Rust rules such as raw pointer manipulation. The unsafe scope is extensively used, especially in standard library, but it is usually wrapped in a "safe" API [3]. By implying safe, the developer assures that no unsafe or undefined behaviours can be made using the API. The Rust compiler will not be able to statically check this safety, so all safety guarantees have to provided by the developer. Even if the risk of undefined behaviour is restricted to specific part of the program, the unsafe scopes, this will still risk enabling unsafe behaviour at run-time which may cause exceptions.

[12] define a semantic model, called RustBelt, for proving soundness of Rust modules which use the unsafe clause but still claim to expose a safe API. Although Rust concepts mostly ensure soundness of developed programs, Rust itself is still being developed and shaped. Thus, RustBelt will help extend Rusts claim for statically checked safety and support the Rust community by locating bugs.

2.5 Scala Programming Language

2.6 Low Level Virtual Machine

Low level virtual machine (LLVM) [14] is an compiler framework which consists of an virtual low-level instruction set. The virtual instruction set capture the primitives commonly used to implementation features in high-level languages. This enables a large set of different high-level

languages to target the LLVM byte-code during compilation. The byte-code resembles assembly code by not guaranteeing any type safety or memory safety. LLVM assumes that the high-level programming level will decide to which degree type safety and memory safety should be enforced.

LLVM creates an IR from this byte-code and apply safe optimisation techniques to it, thus not altering the semantics of the program. LLVM has the ability to link and merge applications written in different high-level languages to one single LLVM byte-code program. The requirement is that the each of the high-level languages' compiler can compile to LLVM byte-code. LLVM can then apply optimisation across the high-level programming language boundaries.

LLVM also support profile-directed optimisation's at run-time. LLVM can take feedback from the executed binary to find hot-paths. A hot-path represent an execution path which is frequently used during run-time e.g. which branch of an if else statement are mostly used. Using this feedback, the LLVM restructures the instructions to improve run-time performance and re-compiles the optimised program to native-code. This is called just-in-time (JIT) compilation and is a part of other higher-level VMs as well. E.g. the java VM optimize at run-time using profile-directed optimisation.

Chapter 3

Design

Chapter 4

Implementation

Chapter 5

Evaluation and Discussion

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Appendix A

Appended Material