High-level GPU programming in Julia

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Abstract

GPUs are popular devices for accelerating scientific calculations. However, as GPU code is usually written in low-level languages, it breaks the abstractions of high-level languages popular with scientific programmers. To overcome this, we present a framework for CUDA GPU programming in the high-level Julia programming language. This framework compiles Julia source code for GPU execution, and takes care of the necessary low-level interactions using modern code generation techniques to avoid run-time overhead.

Evaluating the framework and its APIs on a case study comprising the trace transform from the field of image processing, we find that the impact on performance is minimal, while greatly increasing programmer productivity. The metaprogramming capabilities of the Julia language proved invaluable for enabling this. Our framework significantly improves usability of GPUs, making them accessible for a wide range of programmers. It is available as free and open-source software licensed under the MIT License.

Categories and Subject Descriptors D.3.4 [Programming Languages]: Processors—Code generation, Compilers, Run-time environments

Keywords Julia, GPU, CUDA, LLVM, Metaprogramming

1. Introduction

GPUs can significantly speed up certain workloads. However, targeting GPUs requires serious effort. Specialized machine code needs to be generated through the use of a vendor-supplied compiler. Because of the architectural set-up, initiating execution on the coprocessor is often quite complex as well. Even though the vendors try hard to supply toolchains that support different developer environments and offer convenience functionality to lower the burden, they are essentially playing catch-up.

While coprocessor hardware improves program efficiency, high-level languages are becoming a popular choice because of their improved programmer productivity. Languages such as Python or Julia provide a user-friendly development environment. Low-level details are hidden from view, and secondary tasks such as dependency management and compiling and linking are automatically taken care of.

For users of these high-level languages, jumping through the many hoops of GPU development is often an exceptionally large burden. A lot of low-level knowledge is required, and many of the user-friendly abstractions break down. For example, when using Python to target NVIDIA GPUs using the CUDA toolkit, the developer needs to write GPU kernels in CUDA C, and interact with the CUDA API in order to compile the code, prepare the hardware and launch the kernel. The situation is even worse for languages unsupported by the CUDA toolkit, such as Julia, in which case there are only superficial or no CUDA API wrappers at all.

Ideally, it should be possible to develop and execute high-level GPU kernels without much extra effort: writing kernels in high-level source code, while the interpreter for that language takes care of compiling the necessary functions to GPU machine code. Low-level details should be automated, or at least wrapped in user-friendly language constructs.

This paper presents a framework to target NVIDIA GPUs, and by extent other accelerators, directly in the Julia programming language: Kernels can be written in high-level Julia code. We also created high-level CUDA API wrappers to support the natural use of the CUDA API from within Julia. The framework provides a user-friendly GPU kernel programming and execution interface that automates driver interactions and abstracts GPU-specific details without introducing any run-time overhead. All code implementing this framework is available as open-source code on GitHub.

In Section 2 we describe relevant technologies and the motivation for our work. Section 3 provides an overview of our framework, each component explained in detail in Sections 4 to 6. Finally, we evaluate our work in Section 7.
2. Motivation and Background

2.1 CUDA programming

Executing code on a coprocessor like a GPU requires developers to send specific machine code over to the GPU, prepare the execution environment (configure hardware properties, upload required data to device memory, etc.) and finally start execution. All these operations are performed by calling into the device driver, creating the explicit distinction between host code running on the CPU, responsible for configuring the environment, and device code running on the GPU, performing the actual computations.

The hardware vendor often provides a user-friendly toolchain that takes care of some of these details. In the case of NVIDIA GPUs for example, the CUDA toolkit allows writing GPU kernels in C or C++, and provides system headers that wrap the necessary CUDA driver calls in more user-friendly, language-native constructs. Such toolchains are often only available for systems languages, and still require significant knowledge about the platform and its specifics.

The CUDA toolkit comes with two APIs: the low-level driver API, and the higher-level run-time API implemented on top of the driver API [22]. We have implemented our framework using the driver API, because certain low-level functionality is missing from the run-time API.

Launching a kernel using the driver API consists at least of creating a code module, extracting a function handle and launching the kernel given this handle and other parameters like grid and block dimensions, shared memory, kernel arguments, etc. Code modules are created by sending Parallel Thread Execution (PTX) code containing one or more kernels to the API. PTX code is comparable to traditional CPU assembly code, but it is a virtual Instruction Set Architecture (ISA), translated by the device driver to the target ISA. This hides device-specific properties to improve portability.

2.2 Julia technical computing language

Julia is a dynamic language for scientific computing, designed for performance [3]. By means of aggressive code specialization against run-time types in combination with a Just-in-Time (JIT) compiler using the LLVM compiler infrastructure [19], the compiler is able to emit highly efficient machine code. This makes it possible to write performance-sensitive code in Julia itself, avoiding the classical two-tier architecture (also dubbed “the two language problem” [3]), where application logic is expressed in a high-level language but heavy computations are performed in a low-level programming language like C or C++. To illustrate this point, the entire Julia standard library is written in Julia itself (with some obvious exceptions for the purpose of reusing existing libraries), while still offering good performance.

2.2.1 Compiler overview

Julia code is not statically compiled. When invoking the Julia interpreter to execute a source file, the code will seemingly be executed without a separate compilation step, much like other scripting languages such as Python or R. However, behind the scenes a JIT compiler generates native machine code, employing static code generation techniques to improve performance. In the current situation, this Julia code generation is limited to LLVM-supported CPUs.

Figure 1 shows the main components for compiling and executing Julia source code. First, source code is parsed into an Abstract Syntax Tree (AST) [17]. Then, metaprogramming constructs are expanded (see Section 2.2.3), and type inference takes place, annotating the AST for optimization and code generation purposes. The typed AST is used by the code generator to emit LLVM Intermediate Representation (IR) code, which finally can be compiled to machine code using one of the available LLVM back-ends.

Note that the resulting execution can trigger another compilation. This happens, e.g., when executing a call to a function that was not defined at the point the call was generated. The called function will then be compiled at runtime. On-the-fly compilation is also used to type-specialize functions, triggering recompilation when the arguments’ types change.

Whereas the Julia AST is target-independent, the code generator contains conditional code paths depending on the type of processor. These conditionals take care of platform-dependent functionality, and cope with the fact that LLVM IR is not target independent (due to explicit pointer widths, memory alignment, calling conventions, etc.).

2.2.2 Two-tier GPU support

Although the Julia toolchain cannot generate code for a GPU, it is possible to target such devices in a classical two-tier
**Listing 1.** CUDA C device code for vector addition.

```c
extern "C"
{
  // define a kernel
  __global__
  void vadd(const float *a, const float *b, float *c)
  {
    int i = threadIdx.x + blockIdx.x * blockDim.x;
    c[i] = a[i] + b[i];
  }
}
```

**approach:** write GPU code in a supported language, and use the resulting compiled objects from within Julia.

In the case of an NVIDIA GPU, this means writing the code in CUDA C, compiling it to PTX instructions and using the CUDA APIs to prepare and execute the kernel. As a running example, we consider the simple task of adding two floating-point vectors. Listing 1 contains the CUDA C source code, which can be compiled with the CUDA toolkit’s `nvcc` compiler.

Before executing the resulting PTX object code, the user needs to use the CUDA API to configure the hardware and prepare execution. There exist several unofficial CUDA API wrappers for Julia that target both the CUDA driver and run-time APIs [15, 20], including the CUDA.jl package, the starting point of this work. The wrappers make heavy use of the `ccall` feature of Julia, which allows calling into C code with relative ease. It is noteworthy that these `ccall` expressions are compiled to the same instructions a native C call would be, so the resulting overhead is the same as calling a library function from C code [17].

The kernel from Listing 1 can be launched from within Julia using the existing CUDA driver API wrapper [20]. Although this wrapper exposes the API using familiar Julia mechanics, it is a shallow wrapper in which each expression narrowly maps to a few API calls. This makes the resulting host code verbose and non-obvious, as shown in Listing 2 where underlined keywords are part of the CUDA.jl package, and requires detailed knowledge about the underlying driver API. Our framework automates these interactions, significantly reducing the required host code to that of Listing 3.

**Listing 2.** Julia host code for launching a CUDA kernel using the pre-existing CUDA.jl API wrapper.

```julia
# set-up
dev = CuDevice(0)
ctx = create_context(dev)

# load kernel
md = CuModule("vadd.ptx")
vadd_fun = CuFunction(md, "vadd")

# create some data
dims = (3, 4)
a = round(rand(Float32, dims) * 100)
b = round(rand(Float32, dims) * 100)

gf = CuArray(a)

gb = CuArray(b)

gc = CuArray(Float32, dims)

# execute!
len = prod(dims)
launch(vadd_fun, len, 1, (gf, gb, gc))

# download results
c = to_host(gc)

# verify
@assert a+b == c

# clean-up device memory
free(gf)
free(gb)
free(gc)

# tear-down
unload(md)
destroy(ctx)
```

The macro’s body will be evaluated right after the invocation is parsed. Its argument is passed symbolically, i.e., as an AST, in this case an AST that encodes the Julia expression `foobar(42)`. The return value `output_ast` is also an AST, and gets included in the program’s AST replacing the original subtree of the macro invocation and its arguments, i.e., of the whole expression `@my_AST_transform foobar(42)`. Macros are not limited to transforming ASTs. They can generate and inject arbitrary code where the macro was originally invoked, a feature our framework heavily relies on.

**Generated function** constitute the second metaprogramming interface. These are similar to macros, but they are

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2.2.3 Julia metaprogramming

Julia has strong support for Lisp-like metaprogramming. The language is homoiconic: Code is represented as a datastructure of the language itself. This empowers much of the metaprogramming functionality, as a program can transform and generate its own source code [17].

Code can be generated and evaluated at every point during program execution, and two interfaces allow access to a program’s AST before it is evaluated. The first is a macro, which gets expanded when the code is parsed. The body of the macro is executed during macro expansion, and any argument to the macro is passed symbolically. For example, consider the following macro definition and invocation:

```
macro my_AST_transform(input_ast)
  output_ast = transform(input_ast)
  return output_ast
end

@my_AST_transform foobar(42)
```

The macro’s body will be evaluated right after the invocation is parsed. Its argument is passed symbolically, i.e., as an AST, in this case an AST that encodes the Julia expression `foobar(42)`. The return value `output_ast` is also an AST, and gets included in the program’s AST replacing the original subtree of the macro invocation and its arguments, i.e., of the whole expression `@my_AST_transform foobar(42)`. Macros are not limited to transforming ASTs. They can generate and inject arbitrary code where the macro was originally invoked, a feature our framework heavily relies on.

**Generated function** constitute the second metaprogramming interface. These are similar to macros, but they are
evaluated after type inference. As a result, the AST passed to the generated function now also includes the type of the expressions. This allows generating specialized code, avoiding the run-time overhead of switching between different implementations based on the type of a variable or expression.

Macros and generated functions are useful to extend the language, i.e., to define new syntax that the compiler would otherwise not support. We will also use it to improve performance by replacing potentially recurring run-time overhead with one-time calculations during code generation.

3. System Overview

Adding GPU support to the Julia language involved modifying multiple compiler components and adding significant pieces of functionality. We confined as much functionality as possible to the CUDA.jl package, which only consists of Julia code. The remaining changes are part of the code generator, which is written in C++.

Julia GPU kernels We extended the Julia language by adding the @target macro that will be discussed in more detail in Section 4.2. A developer can use this optional macro to indicate which target a function should be compiled for. Line 2 in Listing 3 illustrates its use for a Julia GPU kernel.

In combination with the @target macro, we added PTX support to the Julia compiler as detailed in Section 4.1. This allows compiling Julia kernel functions to PTX code, which can be then executed by means of the CUDA APIs. Finally, we added intrinsic functions that expose this compiler functionality. This enables any Julia host code to call into the compiler and generate PTX instructions.

CUDA API wrapper Starting from the CUDA.jl Julia package [20], we implemented comprehensive support for launching kernels and all related tasks. We improved the wrapper’s compatibility, making it possible to target non-CUDA hardware with the GPU Ocelot emulator [12]. These contributions are described in Section 5. Although we focused on wrapping the complete API, we also extended the available high-level wrappers to cover one or more API calls with more idiomatic Julia types or expressions. This improves user-friendliness, for when a developer needs to use the API manually rather than rely on the automation infrastructure presented in Section 6.

High-level automation Improving productivity even further, we provide a way to generate API calls rather than requiring the developer to call the API manually. Using Julia’s strong metaprogramming capabilities, we inspect how a kernel is invoked, and generate specialized PTX code together with all necessary API calls as soon as the required type information is known. Listing 3 shows how this makes the process of calling GPU kernels almost fully transparent, without adding any run-time overhead.

4. Julia GPU Kernels

Adding support for writing GPU kernels in high-level Julia code consists of two components: a modified Julia compiler for generating PTX assembly from Julia source code, and a language extension for developers to indicate which functions are meant to be compiled that way.

4.1 PTX code generation

The existing Julia compiler only supports generating code for traditional CPUs. A single code generator compiles the AST to LLVM IR code, with some conditional code paths depending on the type of processor. These conditionals are configured at compile time, which means that each compiled Julia interpreter is tied to a specific platform and processor.

Adding support for emitting PTX code is quite invasive. Firstly, as the Julia code generator needs to generate both PTX instructions and native host code, target selection must happen at run time. Because of how LLVM works, the PTX code will have to reside in a separate code module, isolated from the host module. Secondly, the GPU architecture and execution model differs significantly from the processors currently supported by Julia. Semantic differences in the emitted LLVM IR can be resolved easily with conditional code paths in the code generator. For example, LLVM IR supports the notion of address spaces, and every pointer indicates which address space its pointee lives in. In the case of x86, this is a relatively unused feature, and the Julia code generator always makes use of the default address space 0. PTX code by contrast uses these semantics to differentiate between the different types of device memory, such as global, constant or texture memory. This required modifying the Julia code generator to make sure that the address space property is conserved and appropriate glue code is generated when exchanging values between different address spaces.

Listing 3. Julia source code with high-level GPU kernel and automated driver interactions.

```
1  # define a kernel
2  @target ptx function vadd(a, b, c)
3  i = blockid_x() + (threadid_x()-1) * numBlocks_x()
4  c[i] = a[i] + b[i]
5  end

7  # create some data
8  dims = (3, 4)
9  a = round(rand(Float32, dims) * 100)
10  b = round(rand(Float32, dims) * 100)
11  c = Array(Float32, dims)

13  # execute!
14  len = prod(dims)
15  @cuda (len, 1)
16  vadd(CuIn(a), CuIn(b), CuOut(c))

17  # verify
18  @assert a+b == c
```
A bigger restriction stems from the fact that the GPU and CPU memories are disjoint, i.e., pointers are not interchangeable. The Julia code generator will try to represent values by machine-native types. An integer variable for example will often be lowered to a native integer. However, when the variable hosts a complex object, or its type is dynamic, i.e., not known at compile time to be a singular type, the value will be boxed, heap-allocated, and garbage collected. On a GPU, support for garbage collected objects is hard to implement: The current heap bookkeeping is inherently single-threaded, and lives entirely in CPU memory. So in our framework, we completely depend on Julia to lower data types to its native counterparts that won’t be heap-allocated. If the value cannot be represented natively, and hence would be boxed, compilation is aborted. Although this might seem like a big restriction, kernel code is often reasonably simple, only performing data transformations or other calculations. Additionally, the Julia developers are continuously working on improving the type lowering mechanics, as using native types rather than garbage-collected boxes allows LLVM to reason about these types and therefore to optimize the code better.

This dependence on Julia’s type lowering does not prevent developers from writing kernel code in a dynamic fashion: Variable types only need to be known at compile time to avoid object boxing. Source code can still use dynamically typed variables, and rely on type inference to derive the necessary type information. If at some point a dynamically typed function is invoked with previously unseen types of arguments, this triggers a new compilation. Type inference is performed again, and the resulting machine code is saved for reuse in a method cache.

Out of necessity, we implemented the actual PTX code generation support in the C++ core of the Julia code generator. This facilitates interacting with the LLVM APIs and Julia internals, which are both written in C++. Additionally, this enables reuse of parts of the CPU code generator.

Besides generating the PTX code, executing Julia code on GPUs also requires the hardware to be configured, the code to be uploaded, etc. We decided against implementing this in the C++ code generator, instead extending a Julia package as detailed in Sections 5 and 6. This has a twofold advantage: Maintainability is greatly improved, and the added functionality is only enabled when explicitly importing the package.

The Julia code in this package needs to invoke the code generator to compile certain kernel functions to PTX code. Regular calling mechanics do not apply here, since calling a kernel requires invoking the CUDA APIs. We therefore expose this functionality through compiler hooks. These are intrinsic functions predefined by the Julia compiler that enable Julia host code to call into the code generator. These hooks are not only used to invoke the PTX code generator, but also to initialize and configure the LLVM PTX target, extract the compiled kernel’s symbol name, and other auxiliary tasks.

4.2 @target macro

As the compilation of GPU functions differs significantly from ordinary CPU functions, a developer needs to be able to mark functions as such. We opted for a lightweight language extension: a @target macro to preface a function definition, as shown in Listing 5 on line 3. This macro puts the specified target name as a meta attribute in the AST of the function. The compiler reads this attribute, and uses it to activate the conditional, PTX-specific compilation flow.

5. CUDA API Wrapper

To launch kernels and perform all related tasks, we need access to a wide range of CUDA API functions. Targeting the driver API rather than the higher-level run-time API, we started from the existing CUDA.jl wrapper [20]. This package provides a Julia interface for most API calls, which we extended for our needs. For example, we added support for shared memory and global variables in the form of idiomatic Julia constructs rather than plain API call wrappers.

Additionally, we improved the package’s compatibility by adding support for different versions of the CUDA APIs. The package now also supports the GPU Ocelot emulator [12], which we extended in order to cover all required API calls. Developers can now use the Julia GPU support without having any physical NVIDIA hardware; This is interesting both for ease of development, e.g., on a laptop or a continuous integration server, as well as compatibility, e.g., to support GPUs of different vendors.

As part of the API, we defined intrinsic functions for use within GPU kernels. Some of these intrinsics translate to PTX-specific functionality exposed by means of LLVM intrinsics, e.g., to access the size of and position within the currently active block and grid. Some examples are shown on line 3 of Listing 3. These are essential to GPU kernels, which rely on that very position information to differentiate parallelized computations between individual threads.

Other intrinsics map onto parts of the CUDA device library, libdevice, which contains serialized LLVM IR code implementing common functionality for each generation of GPU [22]. In some cases, this functionality replaces built-in Julia counterparts unfit for GPU execution. For example, the Julia standard library implements most basic trigonometric functions by invoking the openlibm math library. This library is not available for execution on the GPU, however, and it would prove extremely costly to hand control back to the CPU for every invocation. By using libdevice instead, the computation can be performed on the GPU itself.

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1 The new Unified Memory solves this, but moves the synchronization burden to the API, yielding lower performance than manual management [1].

2 A non-standardized ABI and compiler differences hamper interaction with C++ code. In the future, the Cxx.jl package could be used to let an actual C++ compiler generate glue code. Early experiments have yielded interesting results, but the package was not ready for practical use yet.
We implemented most of these intrinsic functions using the experimental LLVM call functionality in Julia. This compiler feature allows a developer to embed raw LLVM IR code within Julia source code, similar to C developers using inline assembly in their C code.

Sometimes, the functional behavior of a @libdevice function or LLVM PTX intrinsic did not conceptually match what a Julia developer would expect. For example, the aforementioned position information within a block or grid is indexed starting with index 0, while Julia arrays are indexed starting from 1. The intrinsics we expose for use within Julia code correct this behavior, making them adhere to Julia conventions. This minimizes the differences between host and device code, and allows the use of idiomatic 1-indexed array expressions in device code, e.g., based on the thread’s position within a block or grid.

6. High-Level Automation

With the PTX compiler support and the CUDA API wrapper package, it is now possible to target NVIDIA GPUs and other accelerators entirely from within Julia. No external compiler is required, and several commonly-used APIs are wrapped using language-native constructs. An application relying on the already described functionality would look like the code in Listing 2 but with the kernel from Listing 1 written in Julia as well. Although this improves usability, knowledge of the CUDA API is still required, and certain inherent restrictions make it difficult for layman developers to successfully execute Julia code on a GPU.

6.1 @cuda macro

To hide the remaining complexity as much as possible, we developed a @cuda macro to prefix kernel calls. The macro uses Julia’s powerful metaprogramming abilities discussed in Section 2.2.3, and mimics the well-known triple angle bracket calling syntax of CUDA C, which looks as follows:

\[
\texttt{vadd}<<<3,4>>>(a, b, c)
\]

Our @cuda macro looks similar, but refrains from using triple angle brackets which the Julia parser does not accept:

\[
\texttt{@cuda\ (3,4) vadd\(a, b, c\)}
\]

Contrary to the CUDA C calling syntax that narrowly maps onto the kernel launch API call, our macro also takes care of specializing and compiling the function, configuring the hardware and launching the kernel. This is realized with minimal developer interactions: using a version of the Julia compiler with PTX support and importing the CUDA.jl package is sufficient to enable this functionality.

Behind the scenes, the @cuda macro results in two phases of processing and code generation, denoted by 1 and 2 in Figure 3. First, when the Julia parser expands the macro invocation from 3 (passing along expression trees encoding the dimension information and the function call) the syntax of the kernel invocation is checked, and code as in 4 is emitted to call the gen_launch generated function.

The generated function implements phase 2, performing most of the actual work. Much like the first-phase macro, the generated function returns code in the form of an AST, but its body is only executed after type inference, when the arguments’ types are known. This type information is crucial. It allows the compiler to emit the exact amount of low-level glue code required for executing the given Julia function on GPU hardware. For our running example, this results in the code marked as 5 in Figure 3.

Using these metaprogramming mechanics rather than ordinary functions has several advantages. First, it allows transparent use of the familiar calling syntax as can be seen in 6. The generated function will replace this with the actually required API interactions from 7. More importantly, it avoids any run-time overhead: Each invocation of the @cuda macro and ensuing call to gen_launch are only executed once for every set of argument types. The resulting code is saved in a method cache, and reused in each subsequent invocation. The macro nor the generated function end up in the final machine code, only the specialized glue code and the necessary CUDA API calls are found there. Combined with Julia’s JIT compiler, this should allow for run-time performance comparable to that of statically-typed, ahead-of-time compiled CUDA C.

6.2 Kernel specialization and compilation

Specializing the GPU kernel consists of generating a type-lowered version, where expression types have been deduced by means of type inference. Generating this function is done by calling into the Julia compiler, using pre-existing hooks. After this, all variables should be statically typed. If this is not the case, the PTX code generator will abort, because it would result in unsupported, heap-allocated boxes.

Given a function’s type-lowered AST, the PTX code generator is invoked using the compiler hooks from Section 4.1. This involves initializing the LLVM PTX back-end (setting the triple, selecting an architecture, . . . ), and generating PTX code for all functions related to the kernel invocation: the kernel function itself, as well as any callee that was not in-lined. This functionality is part of the gen_launch generated function, which is executed during phase 2. Consequently, even when the resulting kernel code will be executed multiple times, this functionality does not need to be re-executed.

Finally, the generated function emits the necessary CUDA API calls for creating a module, loading the PTX code, acquiring a function pointer and launching the kernel. Some of these API calls, such as creating and loading the module, are evaluated at compile time, with the results cached for future invocations. This further reduces the run-time overhead, but only applies to a small number of API calls. For our example, the remaining calls, wrapped with constructs from Section 5 are shown in code fragment 8.
6.3 Argument conversion and management

In addition to compiling and managing the kernel’s code, the generated function also emits code that takes care of synchronizing the kernel’s arguments between the CPU and GPU, as can be seen in fragment (1). This involves allocating and deallocating memory, converting values if necessary, and copying data to and from device memory.

By default, all arguments will be uploaded to the device before execution, and downloaded back to host memory after completion. Often, however, some arguments will only be read from, while others serve as a container for return values. Although this could be deduced through dataflow analysis of the kernel’s function body, we currently require the developer to specify this behavior using wrapper classes. By optionally wrapping arguments with a CuIn, CuOut or CuInOut constructor, as shown in fragment (1) and on line 15 of Listing 3, the developer can force the compiler to generate only the absolutely necessary memory transfers.

7. Evaluation

7.1 Benchmarks

The main contribution of this paper is a framework that compiles high-level Julia code to PTX instructions, including a library that wraps and automates the CUDA API using abstractions that should not result in run-time overhead. Testing our approach using conventional accelerator-oriented benchmarks suites such as Parboil [25] or Rodinia [6] is not ideal: it would mainly stress the quality of the underlying code generator, in our case the LLVM PTX back-end, and it would require porting each benchmark to Julia.

Instead, we evaluate our work by porting a real-life, scientific application that uses GPUs in a multifaceted manner. We selected the trace transform, an image processing algorithm that extracts image descriptors by projecting along straight lines of an image in multiple orientations [18]. The trace transform benchmark features a lot of parallelism, including coarse-grained parallelism for processing different orientations concurrently and more fine-grained parallelism to break up individual projections into semi-independent computations [2]. Moreover, this benchmark has been used before to compare programmer productivity and performance for a wide range of programming languages, including MATLAB, MEX, Octave, Scilab, C++, OpenMP, CUDA, and pure Julia (i.e., for CPUs only).

That existing work provides a well-optimized CUDA implementation and a baseline Julia version. The code for these implementations is available on GitHub under an open-source license. The CUDA version splits the algorithm in five or more separate kernels, depending on the invocation mode. Some of these kernels are simple and independent, while others feature complex computations and use shared memory for inter-thread communication. We re-used the pure Julia version as the starting point for our Julia GPU implementation, and compare it against the C++ with CUDA version to assess a potential loss in performance.

7.2 Methodology

All benchmarks are run on a dedicated 64-bit Debian Linux 3.16 system containing an Intel i7-3770K processor (3.5 GHz, 4 cores, 8 threads) with 16 GB DDR3 main memory, and an NVIDIA GeForce GTX Titan GPU. We compiled C++ sources with GCC 4.9.2, and used CUDA toolkit version 6.0.37 paired with NVIDIA driver version 340.65. All statically compiled C++ and CUDA code is optimized using the compilers’ -O3 flags, disabling any debug functionality.
with `#DDEBUG`. In the case of CUDA code, we specifically compiled for our GPU’s architecture, sm_35. Julia code is executed using our modified version of the compiler, based on the 0.4 development tree from early 2015.

Benchmarks are run multiple times, discarding initial warm-up iterations. We estimate the precision of the measurements by means of the relative uncertainty, calculated on the basis of the standard deviation and mean of a log-normal distribution [7, 21]. It is generally accepted that relative uncertainties below 2% are characteristic of careful measurements [27]. The measurements reported in this paper are the means of a fitted log-normal distribution, with the maximum uncertainty listed in the accompanying captions.

We compare the performance of 5 implementations, as listed in Tables 1 and 2. The first three implementations are part of existing work [2]. The fourth implementation re-uses the (statically compiled) CUDA C kernels from the second C++ version, in combination with the pre-existing CUDA API wrapper to manage driver interactions. The last version uses our framework to its full extent.

### 7.3 Application performance

The most important performance metric is the steady-state execution time. To measure this, we modify the applications and place the main algorithm invocation in a loop that measures the time it takes to execute each iteration.

The results of these measurements are visualized in Figure 3. It shows how the CPU-based implementations scale linearly. By contrast, implementations using the GPU scale superlinearly for small input sizes. This is due to the large constant overhead of configuring the GPU and launching the kernels, irrespective of the input size [2].

The difference between the CPU-only C++ and Julia implementations scales together with the image size, and is caused by deficiencies in the Julia code generator, more specifically unnecessary checks on integer conversions and array bounds [2]. These checks report failure by throwing an exception, which is currently not supported by our PTX code generator. For the time being, we have disabled these checks altogether, therefore avoiding this loss of performance when compiling Julia kernels to PTX code.

In the case of the Julia implementation reusing statically compiled CUDA C kernels, the slowdown compared to C++ with CUDA is 13% for small images, but this drops to 2% for more realistically sized inputs. The constant part of this overhead, contributing more significantly at lower image sizes, can be attributed to lower generated code quality of the inevitable Julia host code between kernel launches. The remaining overhead at larger image sizes comes from argument conversions, copying and converting Julia datatypes before they are uploaded to GPU device memory. As the amount of data to copy scales in terms of the input image size, this overhead does not disappear for larger images.

Finally, the Julia implementation targeting GPUs directly, i.e., with our framework compiling Julia code to PTX code on the fly, only runs slightly slower, resulting in a 1.5% extra overhead for all image sizes (compared to using statically compiled CUDA C kernels in Julia). Detailed measurements using NVIDIA’s profiling utility shows that this overhead is entirely caused by differences in the code quality between code generated by the LLVM back-end we use in our framework and code generated statically by the CUDA toolkit’s `nvcc` compiler. This overhead is hence not introduced by our approach and implementation, and would vanish if LLVM simply became as good as `nvcc` for compiling code to PTX.

We can therefore conclude that the code generated by our automation framework from Section 6 is on par with manual API interactions.

### 7.4 Program initialization

Although steady-state performance will be of most interest to users, it is interesting to consider the build and initialization times required to start an application from its sources. These measurements are shown in Table 1. Where applicable, we measured the time required for statically building an application and any required objects such as GPU kernels, using a single thread for the sake of comparison. In order to determine the initialization time, we inserted code aborting executing after a single warm-up iteration. Subtracting the known steady-state iteration time, this yields the time to initialize and warm-up the application.

| Implementation | Build (s) | Init (s) |
|----------------|----------|----------|
| C++ (CPU)      | 13.36    | 0.002    |
| C++ (CPU) + CUDA (GPU) | 18.71 | 0.012 |
| Julia (CPU)    | 14.43    |          |
| Julia (CPU) + CUDA (GPU) | 1.26 | 14.66 |
| Julia (CPU + GPU) | 15.85 |          |

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**Figure 3.** Execution times of different trace transform implementations (relative uncertainty: 1.59%).
As expected, static compilation takes a significant amount of time, but avoids run-time initialization overhead. Building the C++ with CUDA implementation takes longer, as kernels and some auxiliary support classes need to be build in addition to the main application’s code. In the case of Julia with CUDA, these auxiliary classes are part of the dynamically compiled CUDA API wrapper. Therefore the static build time is shorter than for the C++ with CUDA version.

Compared to statically-compiled C++, dynamically compiled Julia code involves a long initialization time. However, most of this overhead is due to loading auxiliary packages, such as Images.jl for image support and ArgParse.jl for parsing command-line arguments. New versions of Julia are bound to reduce this overhead, as package precompilation is actively being worked on. Compiling kernels at parse time adds only a relatively small initialization overhead of around 8%, increasing the initialization time from 14.66 to 15.85s. This is significantly shorter than the 5.35s added to the C++ build time when statically compiling the CUDA C kernels. Furthermore, the initialization time can be reduced by caching compiled kernels over multiple executions.

### 7.5 Programmer productivity

To assess the programmer productivity, we count the number of source code lines required to port a trace transform implementation to a GPU. As listed in Table 2, targeting a GPU from C++ by using the CUDA system headers and writing kernels in CUDA C requires a significant amount of work. The program grows from 721 to 1184 lines of code, an increase of almost 65%. Out of those additions, only 163 lines concern the core algorithm, which grows from 69 lines to 89 lines of C++ and 143 lines of CUDA C. This illustrates how, in a traditional C++ with CUDA programming environment, most of the porting effort concerns auxiliary tasks not related to the actual computational part of the application.

Using our version of the CUDA.jl wrapper to launch kernels from within Julia, the implementation’s code grows from 359 to 548 lines of code. This addition of 189 lines is far less than what is required to launch the same kernels from C++, as a result of the wrapper package taking care of auxiliary tasks such as error checking and memory management.

If we replace the CUDA C kernels with Julia code and use our framework to compile and execute that code, we benefit from multiple advantages: the kernel implementations are more concise, and most CUDA API interactions are automated. This shortens the application by almost 100 lines compared to the Julia with CUDA version. Most of the porting effort is now concentrated in the core algorithm, which matters most in terms of application performance. On top of that, all code is now written in the same programming language, further lowering the barrier to programming GPUs.

### 8. Related Work

In recent times, many developments have added GPU support to general purpose, high-level languages without depending on a lower-level, device specific language such as CUDA or OpenCL. One popular approach is to host a DSL in the general-purpose language, with properties that allow it to compile more easily for GPUs. For example, Accelerate defines an embedded array language in Haskell [5], while Copperhead works with a functional, data-parallel subset of Python [4]. Parakeet uses a similar Python subset, with less emphasis on the functional aspect [24]. Other research defines entirely new languages, such as Lime [11] or Chestnut [26]. In all these cases, the user needs to gain explicit knowledge about this language, lowering his productivity.

An alternative to defining a new language is directive-based programming within the host language. OpenACC extends C++ [29], but only a select number of compilers can compile it for GPUs. jCudaMP [10] and ClusterJaMP [28] feature OpenMP-like directives in Java, subsequently compiled to low-level device code. Directive-based programming is often portable over multiple devices, but this generality comes at a cost, and complicates low-level optimization [16]. hiCUDA avoids this by defining lower-level device-specific directives, which require the programmer to be familiar with the CUDA data and execution model [13].

Our work allows writing kernels in the high-level source language, hiding the underlying CUDA API from the developer. Rootbeer accomplishes a similar goal within Java, but requires manual build-time actions to post-process and compile kernel source code [23]. Jacc features automatic run-time compilation and extraction of implicit parallelism, but requires the programmer to construct manually an execution task-graph using a relatively heavy-weight API [8]. The new Rust language also gained lightweight GPU support in a manner very similar to our work, featuring a comparable high-level API wrapper on top of the existing OpenCL support [14]. Using the wrapper is mandatory though, while our work attempts to automate most interactions. In addition, all these projects build upon statically typed source languages. Our work allows for dynamically typed kernels, automatically specialized based on argument types. NumbaPro, being a Python compiler, does support dynamically typed kernels [9]. It optionally takes care of API interactions as well, but does not take into account how arguments are used. NumbaPro also uses a custom Python compiler, which significantly complicates the implementation and is currently not fully compatible with the Python language specification.
9. Conclusion and Future Work

We presented a framework for high-level GPU programming in the Julia programming language. It specializes and compiles Julia kernels to PTX code using the LLVM infrastructure. We extended the CUDA.jl API wrapper, adding user-friendly abstractions and improving compatibility, even with non-CUDA hardware. Finally, we support automating all API interactions, greatly improving usability of GPUs.

We demonstrated the viability of our framework by porting a real-life image processing algorithm, and comparing with pre-existing C++ and CUDA implementations. The performance impact of writing GPU kernels in Julia is negligible, while the required programmer effort is significantly reduced. Boilerplate API interactions have disappeared, and users can focus on porting time-consuming computations.

Our work makes it possible to write portable, high-performance GPU code with low effort. It could be used to port high-level functionality from Julia’s standard library, making it possible to transparently use any available GPU. Extensions to our framework may be required in order to improve compatibility with boxed objects and automatically detect the use of arguments, but in its current state it already proved useful for porting real-life applications.

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References

[1] Acceleware. CUDA 6.0 Unified Memory performance, 2014.
[2] T. Besard, B. De Sutter, A. Frias-Velázquez, and W. Philips. Case study of multiple trace transform implementations. Int. Journal of High Performance Computing Applications, 2015.
[3] J. Bezanson, A. Edelman, S. Karpinski, and V. B. Shah. Julia: A fresh approach to numerical computing. arXiv preprint arXiv:1411.1607, 2014.
[4] B. Catanzaro et al. Copperhead: Compiling an embedded data parallel language. ACM SIGPLAN Notices, 46(8):47–56, 2011.
[5] M. M. Chakravarty et al. Accelerating Haskell array codes with multicore GPUs. In Workshop on Declarative Aspects of Multicore Programming, pages 3–14, 2011.
[6] S. Che et al. Rodinia: A benchmark suite for heterogeneous computing. In Int. Symp on Workload Characterization, pages 44–54. IEEE, 2009.
[7] D. M. Ciemiewicz. What do you ‘mean’: Revisiting statistics for web response time measurements. In Computer Measurement Group Conf., pages 385–396, 2001.
[8] J. Clarkson, C. Kotselidis, G. Brown, and M. Luján. Boosting Java performance using GPGPUs. arXiv preprint arXiv:1508.06791, 2015.
[9] Continuum Analytics. NumbaPro Python compiler, 2015.
[10] G. Dotzler, R. Veldema, and M. Klemm. jCudaMP: OpenMP-Java on CUDA. In Int. Workshop on Multicore Software Engineering, pages 10–17, 2010.
[11] C. Dubach et al. Compiling a high-level language for GPUs. ACM SIGPLAN Notices, 47(6):1–12, 2012.
[12] N. Farooqui et al. A framework for dynamically instrumenting GPU compute applications within GPU Ocelot. In Workshop on General Purpose Processing on Graphics Processing Units, pages 1–9. ACM, 2011.
[13] T. D. Han et al. hiCUDA: High-level GPGPU programming. IEEE Trans. on Parallel and Distributed Systems, 22(1), 2011.
[14] E. Holk et al. GPU programming in Rust: Implementing high-level abstractions in a systems-level language. In Parallel and Distributed Processing Symp. Workshops & PhD Forum, 2013.
[15] T. Holy et al. Julia wrapper for CUDA runtime API. https://github.com/JuliaGPU/CUDA.jl 2015.
[16] T. Hoshino et al. CUDA vs OpenACC: Performance case studies with kernel benchmarks and a memory-bound CFD application. In Int. Symp. on Cluster, Cloud and Grid Computing, pages 136–143, 2013.
[17] Julia developers. Julia documentation, 2015.
[18] A. Kadyrov and M. Petrou. The trace transform and its applications. IEEE Trans. on Pattern Analysis and Machine Intelligence, 23(8):811–828, 2001.
[19] C. Lattner and V. Adve. LLVM: A compilation framework for lifelong program analysis & transformation. In Int. Symp. on Code Generation and Optimization, pages 75–86, 2004.
[20] D. Lin et al. Julia programming interface for CUDA. https://github.com/JuliaGPU/CUDA.jl 2015.
[21] J. R. Mashey. War of the benchmark means: time for a truce. ACM SIGARCH Computer Architecture News, 32(4), 2004.
[22] NVIDIA. CUDA Toolkit documentation, 2015.
[23] P. C. Pratt-Szeliga et al. Rootbeer: Seamlessly using GPUs from Java. In Int. Conf on High Performance Computing and Communication, pages 375–380, 2012.
[24] A. Rubinsteyn et al. Parakeet: A just-in-time parallel accelerator for Python. In USENIX Conf. on Hot Topics in Parallelism, pages 14–14, 2012.
[25] J. A. Stratton et al. Parboil: A revised benchmark suite for scientific and commercial throughput computing. Center for Reliable and High-Performance Computing, 2012.
[26] A. Stromme et al. Chestnut: A GPU programming language for non-experts. In Int. Workshop on Programming Models and Applications for Multicores and Manycores, 2012.
[27] J. Taylor. An Introduction to error analysis: The study of uncertainties in physical measurements. University Science Books, 2nd edition, 1997.
[28] R. Veldema, T. Blass, and M. Philippsen. Enabling multiple accelerator acceleration for Java/OpenMP. In USENIX Workshop on Hot Topics in Parallelism (HotPar’11), Berkeley, CA, pages 1–6, 2011.
[29] S. Wienke et al. OpenACC: First experiences with real-world applications. In Proc of the Int. Conf. on Parallel Processing, pages 859–870, 2012.