

Seminar Report

Introduction to Performance Engineering in Rust

Lars Quentin

MatrNr: 21774184

Supervisor: Dr. Artur Wachtel

Georg-August-Universität Göttingen
Campus-Institut Data Science / GWDG

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Abstract

Due to its high security focus while being a modern systems programming language, Rust is a promising choice for performance critical applications in the field of High Performance Computing (HPC). This report covers an introduction to the methodology of performance engineering using Rusts still developing ecosystem. It was done using the concept of problem based learning, where, using the example of quadratic matrix multiplication, many concepts of performance engineering were explored. This covers micro- and full benchmarking and profiling, assembly analysis, compiler optimizations and an small introduction to single threaded SIMD parallelism as well as multi threading. While the ecosystem is still experimental and ever-changing, the tooling available is already sufficient for thorough performance analysis.

Statement on the usage of ChatGPT and similar tools in the context of examinations

In this work I have used ChatGPT or a similar AI-system as follows:

- ☒ Not at all
- ☐ In brainstorming
- ☐ In the creation of the outline
- ☐ To create individual passages, altogether to the extent of 0% of the whole text
- ☐ For proofreading
- ☐ Other, namely: -

I assure that I have stated all uses in full.

Missing or incorrect information will be considered as an attempt to cheat.

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List of Abbreviations

ADT Algebraic Data Types

CI Continuous Integration

HPC High-Performance Computing

IR Intermediate Representation

I/O Input / Output

IoT Internet of Things

KDE Kernel Density Estimation

LLVM Low Level Virtual Machine

LTO Link Time Optimization

PBL Problem-Based Learning

PDF Probability density function

PGO Profile Guided Optimization

RAII Resource acquisition is initialization

SIMD Single Instruction Multiple Data

1 Introduction

1.1 Motivation

From a programming language perspective, High-Performance Computing (HPC) is dominated by code written in C, C++ or Fortran as these provide the low level control and optimization capabilities common in tightly-optimized code. However, as Rust was initially designed as a modern, memory-safe C++ replacement, it could be a valid choice for any kind of performance-critical code.

Instead of just providing yet another taxonomy of successful HPC projects in Rust, this report will rather provide an introduction to the topic on performance engineering in Rust, implicitly covering the current state of the ecosystem while providing a short explanation of each of the common concepts. Instead of just providing an enumeration of techniques, it rather uses Problem-Based Learning (PBL) to introduce the techniques just-in-time when they are relevant, providing a more coherent learning progression.

Problem-Based Learning can be difficult. The problem has to be

- Small enough to fit the scope of a report
- Complex enough to cover most of the concepts of real-life performance engineering
- Interesting enough to keep readers engaged in the topic

For this report, we decided to analyze matrix multiplications. More than just a toy-problem, the matrix multiplication is at the core of all deep learning frameworks. As the parameter count steadily increases into the trillions [1], fast matrix multiplications become evermore important for today's frameworks.

1.2 Rust

Rust [2] is a systems programming language initially released by Mozilla Research in 2015. It was designed as a memory safe alternative for C++ in Servo [3], which is the web rendering engine used in Firefox. Rust's main goal is to provide memory safety while having an on-par performance with other systems languages such as C or C++.

Having memory safety is paramount, as most security issues in traditional C/C++ codebases are a result of using a memory-unsafe language. To quote the overview by Alex Gaynor [4]

- Android [5]: "Our data shows that issues like use-after-free, double-free, and heap buffer overflows generally constitute more than 65% of High & Critical security bugs in Chrome and Android."
- Android's bluetooth and media components [6]: "Use-after-free (UAF), integer overflows, and out of bounds (OOB) reads/writes comprise 90% of vulnerabilities with OOB being the most common."

- iOS and macOS [7]: "Across the entirety of iOS 12 Apple has fixed 261 CVEs, 173 of which were memory unsafety. That's *66.3%* of all vulnerabilities." and "Across the entirety of Mojave Apple has fixed 298 CVEs, 213 of which were memory unsafety. That's *71.5%* of all vulnerabilities."
- Chrome [8]: "The Chromium project finds that around *70%* of our serious security bugs are memory safety problems."
- Microsoft [9]: "*~70%* of the vulnerabilities Microsoft assigns a CVE each year continue to be memory safety issues"
- Firefox's CSS subsystem [10]: "If we'd had a time machine and could have written this component in Rust from the start, 51 (*73.9%*) of these bugs would not have been possible."
- Ubuntu's Linux kernel [11]: "*65%* of CVEs behind the last six months of Ubuntu security updates to the Linux kernel have been memory unsafety."

Furthermore, it is now adapted by many big tech firms such as Amazon [12], Google [13], Meta [14], and Microsoft [15]. Lastly, in december 2022, it became the first language other than C and Assembly supported for Linux kernel development [16].

1.2.1 Why Rust is a good fit for HPC

Basically, one can think of Rust as a modern dialect of C++ enforced by the compiler. It uses Resource acquisition is initialization (RAII) internally to ensure memory safety, while references are roughly equivalent to `std::unique_ptr`.

Especially relevant is the great interoperability with other languages. It supports easy integration with C++ using `bindgen` [17], which is developed by the Rust core team. Rust also allows for easy embedding into Python code using `PyO3` [18], allowing for high-performant native extensions.

Furthermore, it allows for very low level control, even to the extend of bare metal deployment support. Due to Rusts aforementioned RAII-like memory management model, the runtime has no need for a garbage collector. One can even bring their own memory allocator and do raw pointer arithmetic if required. Lastly, Rust supports architecture based conditional compilation which makes it possible to write fast programs leveraging modern CPU instructions while providing portable alternatives. To support bare metal, OS-less development, Rust's standard library is split into 3 tiers:

- **core**: The `core` library provides essential types and functionality that do not require heap memory allocation.
- **alloc**: The `alloc` library builds upon the `core` library but expects heap-allocations, thus supporting things such as dynamically sized vectors.
- **std**: The `std` library is the highest-level tier, requiring not only a memory allocator but also several OS capabilities such as I/O management.

Although Rust itself is a relatively new language, its compiler supports most modern compiler optimizations. This is possible through Low Level Virtual Machine (LLVM). Instead of producing native assembly for all architectures, the compiler just provides a LLVM frontend generating LLVM Intermediate Representation (IR) which then gets translated to native code by LLVM.

Lastly, it supports many modern functional concepts such as immutability by default, flat traits instead of deep inheritance, exhaustive pattern matching with Algebraic Data Types (ADTs) sum types as well as providing alternatives to nullability, which is commonly known as the billion dollar mistake [19]. Its language design is in fact so popular that according to the yearly StackOverflow surveys it was voted as the most loved language for the 7th year in the row [20].

1.3 Quadratic Matrix Multiplication

Let $A, B \in \mathbb{R}^{n \times n}$, $n \in \mathbb{N}$. Then $C \in \mathbb{R}^{n \times n}$ is defined as

$$C_{ij} := \sum_{k=1}^n A_{ik} \cdot B_{kj}.$$

One can think of C_{ij} as the dot product of the i -th row of A and the j -th column of B .

1.4 Structure

This report is structured as follows: Section 2 will explore a simplified version of the matrix multiplication problem where the dimension is fixed. Here, the focus will be set on microbenchmarking, full application benchmarking, and assembly analysis. Section 3 will then explore the full matrix multiplication, exploring the topics of profiling, compiler optimizations, cache oblivious as well as how to benchmark in noisy environments. Section 4 will provide a short introduction of parallelism. Lastly, section 5 concludes this report by providing an overview of all shown tools as well as further ressources.

2 Fixed Size Matrix Multiplication

To start off with a simplified problem, this section focuses on a fixed quadratic matrix size of $n = 3$. Using the mathematical definition, this can be trivially implemented:

```

1 fn matmul(a: Vec<Vec<f32>>, b: Vec<Vec<f32>>) -> Vec<Vec<f32>> {
2     let mut result = vec![vec![0.0; 3]; 3];
3     for i in 0..3 {
4         for j in 0..3 {
5             for k in 0..3 {
6                 result[i][j] += a[i][k] * b[k][j];
7             }
8         }
9     }
10    result
11 }
12 fn driver_code(a: Vec<Vec<f32>>, b: Vec<Vec<f32>>, c: Vec<Vec<f32>>)
13     -> Vec<Vec<f32>> {
14     matmul(matmul(a, b), c) // D := A * B * C
15 }

```

Listing 1: Naive implementation of a 3×3 matrix multiplication.

The `Vec` arguments are currently passed as a call-by-value, which means that the whole vector gets copied onto the function’s stack. Intuitively, this could be improved by using call-by-reference semantics, which just copies the pointer instead of the underlying data. Theoretically, this should result in a performance improvement. In reality, it is very hard to predict actual performance. Thus, some benchmarking is required. In order to measure the performance, either microbenchmarking or full application benchmarking can be used.

2.1 Microbenchmarking

Microbenchmarking is the performance evaluation of small isolated functions. In the Rust ecosystem, there are two obvious solutions for microbenchmarking: Rust’s native `cargo bench` as well as `criterion.rs`, which is the modern canonical benchmark library.

Native Benchmarking Cargo, Rust’s package manager, supports benchmarking natively through the `cargo bench` [21] subcommand. Unfortunately, this is still experimental, thus only part of the unstable nightly Rust versions. Furthermore, no clear roadmap to stability exists [22].

`cargo bench` is a very lightweight microbenchmarking solution. It provides no integrated regression testing nor any kind of visualization or plotting. The 3rd-party `cargo-benchcmp` [23] utility can be used to compare different benchmarks.

Criterion The other solution is `criterion.rs` [24], which is also available in stable Rust. It uses basic statistical outlier detection to measure regressions and their significance. Furthermore, it blocks constant folding using the `criterion::black_box`, which is described as a “function that is opaque to the optimizer, used to prevent the compiler from optimizing away computations in a benchmark” [25]. It automatically generates HTML reports with plots using `gnuplot`. For benchmark comparisons, the `cargo-critcmp` [26]

program can be used.

As there is currently no active development in `cargo bench`, criterion should always be the preferred solution for microbenchmarking.

2.2 Full Application Benchmarking

There are several solutions for benchmarking whole applications, especially as they are usually agnostic to the application's programming language. But to stick to the modern Rust ecosystem, this report will focus on Hyperfine [27], a very actively developed command-line benchmarking tool written in Rust.

From a simplified perspective, full application benchmarking is quite trivial. First, take a timestamp of the current time. Then, run the command to be benchmarked. Afterwards, take a new timestamp. The time delta is the benchmark time. But beyond this core functionality, Hyperfine supports many important and fundamental features for proper benchmarking and analysis.

```

▶ hyperfine --warmup 3 'fd -e jpg -uu' 'find -iname "*.jpg"'
Benchmark #1: fd -e jpg -uu
  Time (mean ± σ):      329.5 ms ±   1.9 ms    [User: 1.019 s, System: 1.433 s]
  Range (min ... max):  326.6 ms ... 333.6 ms    10 runs

Benchmark #2: find -iname "*.jpg"
  Time (mean ± σ):      1.253 s ±  0.016 s    [User: 461.2 ms, System: 777.0 ms]
  Range (min ... max):  1.233 s ... 1.278 s    10 runs

Summary
  'fd -e jpg -uu' ran
    3.80 ± 0.05 times faster than 'find -iname "*.jpg"'
▶

```

Figure 1: An example picture of Hyperfines output comparing `fd` and `find` [27]

Firstly, Hyperfine supports out of the box statistical analysis and outlier detection. Since it can assume that the program run times are approximately equal, benchmark times are normal distributed. Thus, by fitting a normal distribution over all runs and computing its confidence interval, it can detect any outliers. Secondly, it allows for warmup runs and cache-clearing commands¹ between each run. Warmup runs are useful to fill caches such as the page cache for disk I/O. Lastly, it supports further analysis by providing an export to various formats, such as CSV, JSON, Markdown or AsciiDoc, which can then be analyzed programmatically. Hyperfines repository contains several python scripts for basic visualization [29], which can be used as a starting point for further analysis.

2.3 Performance Optimization

For the benchmarking, the aforementioned `criterion.rs` benchmarking framework is used. The benchmark was done on a Dell Latitude 7420 with an Intel i5-1145G7 and 16GB of LPDDR4 RAM, compiled with rustc 1.72.0. The CPU idle was around 1%.

¹such as `echo 1 > /proc/sys/vm/drop_caches` to free the page cache [28].

2.3.1 Call By Reference

Although the data part of `Vec<>` is stored on the heap² the stack-part is still very complex, since it has to keep track of several things such as the current size and its current maximal capacity. More importantly, the `Vec<>` struct has a bigger memory footprint than a pointer. Thus, using Call-By-Reference should improve the performance by requiring less memory copies! In Rust, this can be archived using the `&` operator:

```

1 fn matmul(a: &Vec<Vec<f32>>, b: &Vec<Vec<f32>>) -> Vec<Vec<f32>> {
2     /* Only the signature changes... */
3 }
4 fn driver_code(a: Vec<Vec<f32>>, b: Vec<Vec<f32>>, c: Vec<Vec<f32>>())
5     -> Vec<Vec<f32>> {
6     matmul(matmul(a, b), c) // D := A * B * C
7 }

```

Listing 2: Changing the signature to Call-By-Reference semantics with references.

Using the default criterion settings³, the following results were benchmarked:

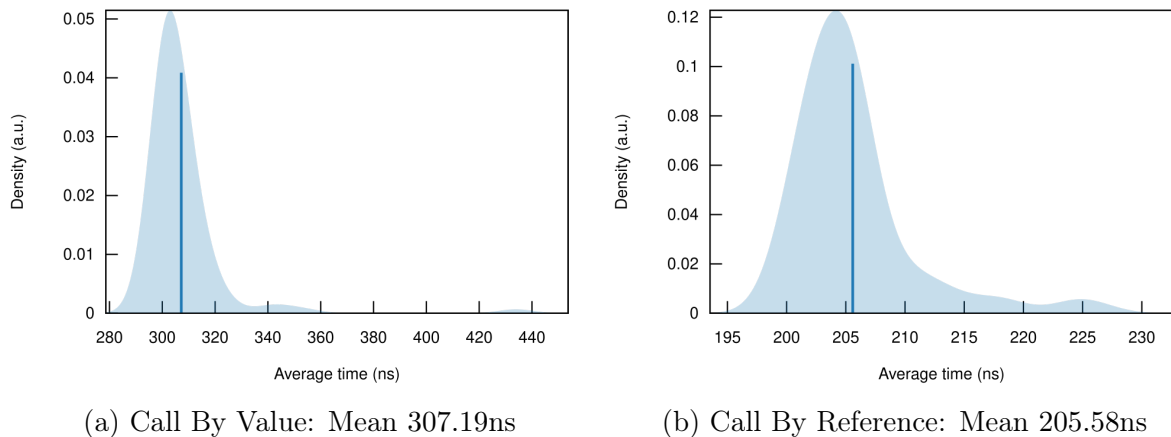


Figure 2: Comparisons of the PDFs computed using KDE for Call-By-Value and Call-By-Reference.

According to the benchmarks, this change alone resulted in a 49.426% mean increase! Note that the full metric table is included in the appendix.

There is one more obvious possible improvement to try: In this code, Rust’s `Vec<>`, a dynamically sized, heap allocated vector is used. This could be replaced with a normal C-type array.

²Since `Vec<>` are dynamically resizable, the absolute size can’t be known at compile time.

³Default Rust Release build

2.3.2 Primitive Stack Arrays

Compared to static arrays, `Vec<>` has much overhead. Firstly, since its size is not known at compile time, it performs several run-time bounds checks ⁴. Next, it has to be heap-allocated, which can be way more expensive and results in worse memory locality. Lastly, `Vec<>` is a complex struct with many functions and features, which in turn results in more computation required.

This is the code using primitive stack arrays instead of the more sophisticated, dynamically allocated vectors:

```

1 fn matmul(a: &[[f32; 3]; 3], b: &[[f32; 3]; 3], result: &mut [[f32; 3]; 3]) {
2     for i in 0..3 {
3         for j in 0..3 {
4             for k in 0..3 {
5                 result[i][j] += a[i][k] * b[k][j];
6             }
7         }
8     }
9 }
10
11 fn driver_code(a: &[[f32; 3]; 3], b: &[[f32; 3]; 3], c: &[[f32; 3]; 3],
12               res_buf: &mut [[f32; 3]; 3]) {
13     let mut temp = [[0.0; 3]; 3];
14     matmul3(a, b, &mut temp);
15     matmul3(&temp, c, res_buf);
16 }

```

Listing 3: Changing the signature to Call-By-Reference semantics with references.

Here are the results, compared to the initial version:

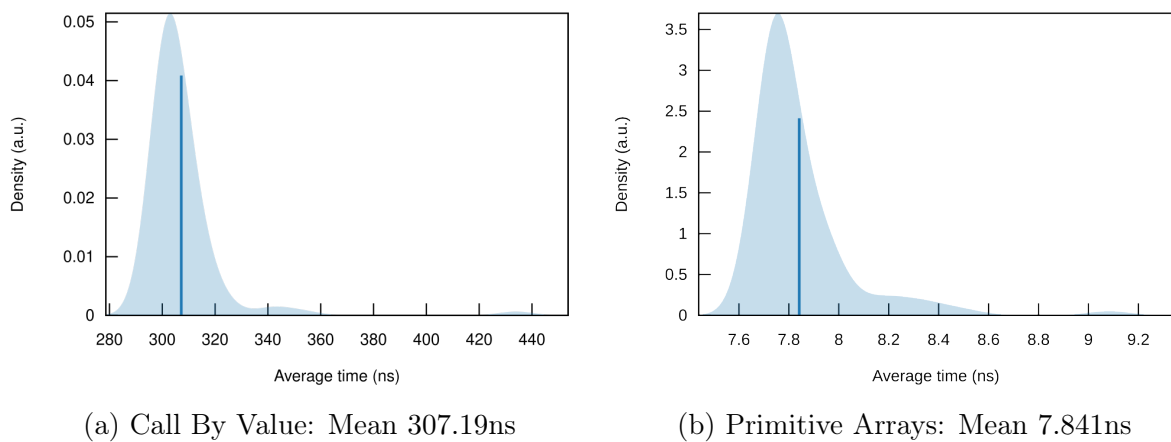


Figure 3: Comparisons of the PDFs computed using KDE for the initial version and the one using primitive arrays.

⁴This can be partially avoided. For more information, see the bounds checks cookbook [30]

This results in a staggering 3831.27% mean increase! Once again, note that the full metric table is included in the appendix.

There are several possible explanations for those results. It could be that the bounds check ruin the instruction pipelining. But the main reason is most likely that the prior version requires an expensive heap allocation for the return value while the static arrays are already preallocated on the stack ⁵. Now that we did all high-level optimizations, the next step would be to optimize on the assembly level. The next section will show how to use proper tooling for assembly level optimization in Rust.

2.4 Assembly Optimizations

Modern compilers, such as the LLVM based `rustc`, do a lot of optimization for performance. This results in vastly different assembly when comparing unoptimized code (`-O0`) to their optimized counterpart (`-O3`). Thus, it often makes sense to look at the assembly for hot code paths⁶. Naively, one could just look at the whole binary and decode the bytes into their instructions. This is neither useful nor reasonable for large programs to analyze. Instead, in this section, two different ways to analyze assembly will be analyzed: The well known Compiler Explorer [31] as well as the `cargo-show-asm` crate [32].

Compiler Explorer Compiler Explorer [31] is an online development environment initially developed by Matt Godbolt, primarily used for analysis of C and C++ applications. It was started in 2023 for optimizing financial quantitative analysis algorithms. Compiler Explorer supports over 30 different languages; from typical high performance languages such as C, C++ and Fortran, bytecode languages such as Python and Java to more niche languages such as Haskell and Solidity. Additionally, one can compare different compilers (for example `gcc`, `clang` and `msvc` for C applications) and manually specify different compiler arguments such as `-Osize` instead of `-O3`. Since it can also be hosted on-premise, proprietary and other custom compilers can be added if needed.

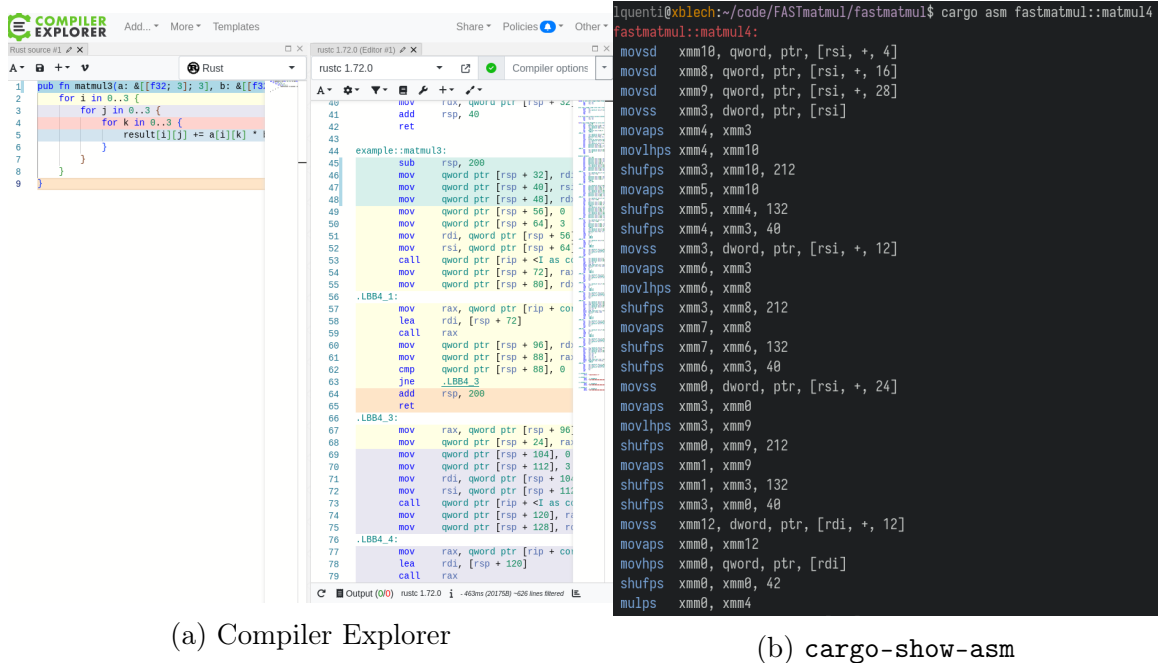
Its main feature is the color coding; Compiler Explorer assigns each function line to a specific color. The same color will then be used in the assembly window, providing an intuitive mapping and an good overall user experience. Unfortunately, it does not support multiple files and hasn't any dependency management ⁷. To summarize, Compiler Explorer is the best fit for small, single file programs. For larger applications, the next tool can be used.

cargo-show-asm `cargo-show-asm` [32] is a more minimalist, less polished console application for analyzing assembly. It works with any rust code base, no matter the size or amount of dependencies. Instead of showing the assembler for all functions, one can query single functions as an CLI parameter. Lastly, instead of the architecture specific assembler code it can also return the LLVM IR instead.

⁵Further analysis could be done through statistical profiling, which will be explained later. But since it doesn't help explaining performance engineering concepts, it is left as an exercise to the reader.

⁶Code paths are 'hot' when they are executed very frequently, therefore crucial for the overall performance.

⁷Although one could work around this restriction by installing all dependencies globally on a self hosted instance.



(a) Compiler Explorer

(b) cargo-show-asm

Figure 4: Two applications to analyze Rust assembly: Compiler explorer and cargo-show-asm.

Next, two common compiler optimizations are covered: Loop Unrolling and Function inlining.

2.4.1 Loop Unrolling

On the surface, loop unrolling is a simple concept: If the number of loop iterations are known at compile time, replicate the inner code that amount of time. This has multiple benefits. Firstly, it reduces the number of comparisons and jumps made in every iteration. Secondly, it allows for easier pipelining since there is no need for path prediction anymore! The main drawback is that code duplication obviously increases binary size.

Looking at the assembly, loop unrolling was already applied in our case. But if the compiler did not unroll the function, there are two main ways to force it manually:

- `Unroll [33]` is a Rust macro to unroll the applications at compile time by replacing the unrolled rust code in preprocessing. Currently, it can just detect loops with integer literal bounds.
- For more sophisticated loops, LLVM can be configured to more aggressively apply loop unrolling. This is controlled by the `-unroll-threshold` parameter⁸.

As an important remark, do not manually apply loop unrolling without benchmarking, as it can worsen performance by consuming too much of the L1 CPU instruction cache.

2.4.2 Function Inlining

The next, very common compiler optimization is function inlining. Instead of jumping into a subroutine, executing it, and then returning to the previous instructions it places

⁸So to apply it with `rustc`, use `-C llvm-args=-unroll-threshold=N` where `N` is an integer.

the assembly of the subroutine into the outer function. On the upside, this eliminates the calling overhead (such as moving arguments into registers) specified by the calling convention⁹. As already mentioned above, function inlining can also worsen performance though increased binary size and consequently less efficient cache utilization.

In our case, it was not applied. But it can be applied manually with the `#[inline(always/never)]` attribute [34].

After covering benchmarking and assembly analysis, we can now approach the harder problem of variadic size matrix multiplication!

3 Variadic Size Matrix Multiplication

Now, after having a simplified toy problem, lets say you get the following task:

“Our department has built a deep learning framework in Rust that inferences too slow. Please try to optimize the overall performance of this project”

Before being able to optimize the code, one has to first ask the following question: Why is it so slow? In order to answer this question, profiling is needed.

3.1 Profiling

Profiling is used to find out which parts of the program are executed frequently enough to effect runtime performance¹⁰. Since Rust produces normal binaries, most traditional profilers just work, including common ones such as Linux `perf` [35] and `cachegrind` [36]. See the profiling section in the Rust Performance Book for an more exhaustive list [37].

Since rust supports polymorphism¹¹ name mangling occurs. As assembly labels have to be unique, name mangling is a technique used to map all polymorphic instances of a function to an unique assembler label. If the profiler doesn't support unmangling natively, `rustfilt` can be used manually [38].

In this chapter, we use `cargo-flamegraph` [39] and later `iai` [40] for profiling.

3.2 Cargo Flamegraph

Cargo flamegraph [39] is a statistical profiler that creates a flamegraph to analyze. In order to understand the result, one needs to understand how statistical profilers work internally. A statistical profiler works by interrupting the program randomly using the kernels interrupt system¹². After interrupting, it looks at the stack frame, finding out which function stack is currently called. This is a single data point. Now, using a monte

⁹Interestingly, Rust does not have a default non-FFI calling convention for performance benefits. Instead, it requires all dependencies to be compiled with the same version, which is the canonical way when the package manager `cargo` is used.

¹⁰So called **hot paths**.

¹¹Both ad-hoc polymorphism through traits and parametric polymorphism based on generics.

¹²Cargo flamegraph uses `perf` and `dtrace` internally.

carlo approach, a statistical profiler can approximate how much time is spent in each function by taking many measurements.

A flamegraph is a visualization of the stack frames. The wider the current stack frame, the more often those functions were called then interrupted. One layer got called by the layer below. Here is an example of an flamegraph:

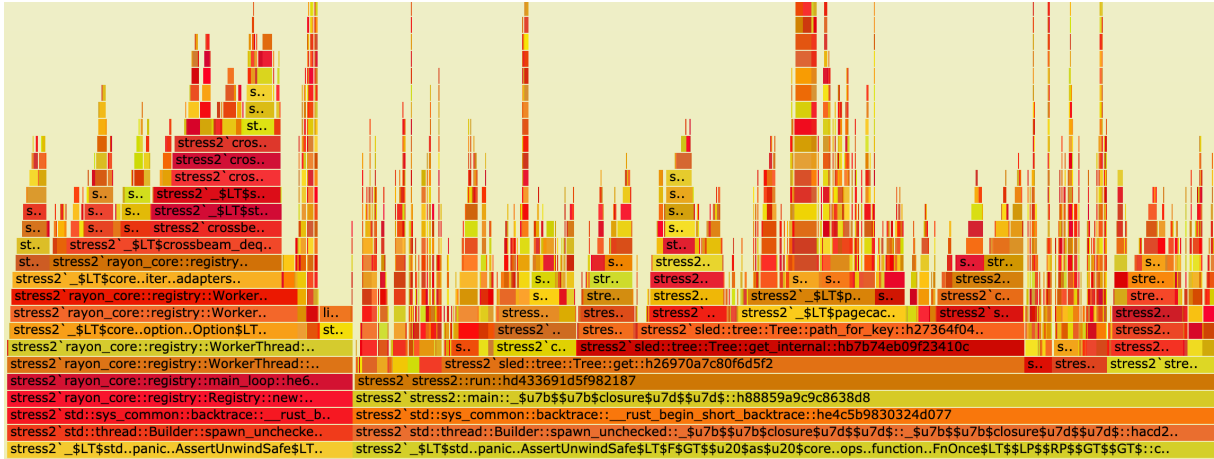


Figure 5: An example flamegraph generated from Rust code [39].

For our fictional deep learning framework, let's assume that the result was a slow $N \times N$ variadic size matrix multiplication! For the benchmarks, we use $N = 1024$.

3.3 Applying Previous Knowledge

Lets say that the matrix multiplication function looks as follows:

```

1 fn matmul(a: Vec<Vec<f32>>, b: Vec<Vec<f32>>) -> Vec<Vec<f32>> {
2     let n = a.len();
3     let mut result = vec![vec![0.0; n]; n];
4     for i in 0..n {
5         for j in 0..n {
6             for k in 0..n {
7                 result[i][j] += a[i][k] * b[k][j];
8             }
9         }
10    }
11    result
12 }
```

Listing 4: The unoptimized Rust code providing the variadic size quadratic matrix multiplication

Applying the knowledge of our previous chapters, we can already refactor it into the following:

```

1 fn matmul(a: &[f32], b: &[f32], result: &mut [f32], n: usize) {
2     for i in 0..n {
3         for j in 0..n {
4             for k in 0..n {
5                 result[i * n + j] += a[i * n + k] * b[k * n + j];
6             }
7         }
8     }
9 }

```

Listing 5: The code optimized analogously to chapter 2.

But before benchmarking this code, there are further free improvements to be had by configuring the compiler to maximize performance.

3.4 Compiler Optimizations

There are several performance optimizations that should be enabled if performance is a high priority:

- **Release Builds:** This is by far the biggest improvement. If one does not use the release build¹³ the code is not optimized. This enables several general optimizations as well as automatic vectorization.
- **LLVM Link Time Optimization (LTO):** LTO enabled further, intermodular optimizations during the link stage. While this could improve code by optimizing beyond library bounds, it increases compile time, which is why it is disabled by default.
- **Compiling for Native Architecture:** When compiling for the native architecture¹⁴ the compiler can use more specialized instructions that are not available on every processor such as bigger vector registers for SIMD. Note that this makes the code incompatible with older processor generations.
- **Using a single LLVM codegen unit:** Codegen units are analogous to translation units. This means that, when changing a single file, just the codegen unit in that file has to be recompiled. Therefore, optimizations can't be done beyond codegen unit bounds! Using a single codegen for the whole project allows the compiler to more aggressively optimize globally. Note that this effectively disables partial compilations.
- **Profile Guided Optimization (PGO):** PGO could furthermore be used for more effective branch prediction¹⁵.

¹³With `cargo build -release`.

¹⁴Using the `RUSTFLAGS` environment variable, i.e. `RUSTFLAGS="-C target-cpu=native" cargo build -release`.

¹⁵This is out of the scope for this project, for an introduction see how the compiler team used it on `rustc` [41]

Here are the results, the full table can be found in the appendix:

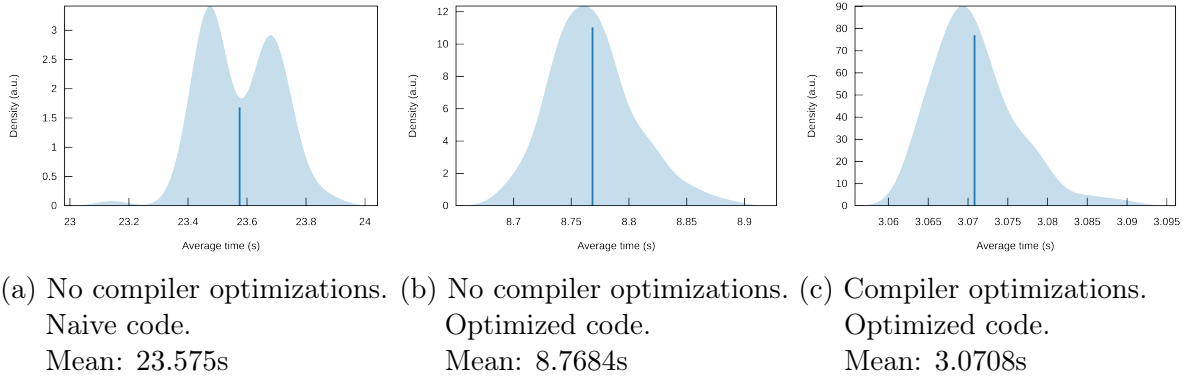


Figure 6: Performance comparison between unoptimized code, optimized code and optimized code with compiler optimization enabled.

For the next and last optimization, some further theory is needed.

3.5 Cache-oblivious Algorithms

When doing a standard matrix multiplication $C := A \cdot B$, A traverses the matrix in row-major order and B traverses the matrix in column-major order. Since the memory is aligned in row-major order, in every step of B we get a cache miss for large sizes of B .

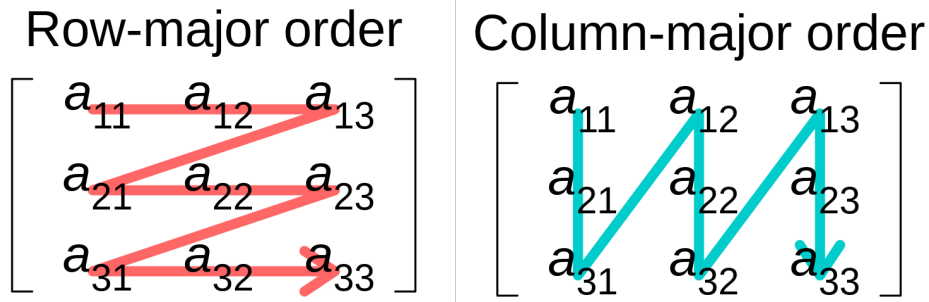


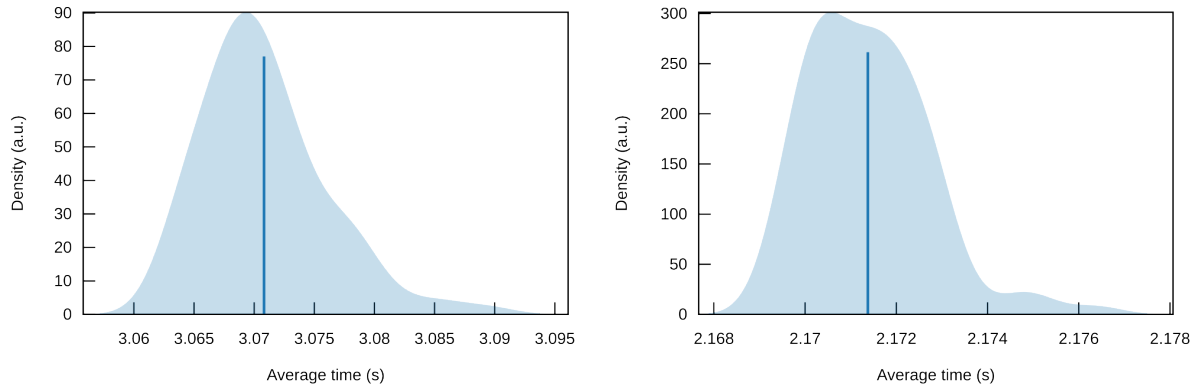
Figure 7: A visualization of row- and column-major order.

A possible solution could be to compute $A \cdot B^T$ instead by transposing B . Then, C_{ij} is computed as row A_i times **row** B_j ! Unfortunately, since we have to actually compute the transpose beforehand, this requires $\Theta(n^2)$ precompute.

Naturally, two questions arise:

1. Does it improve speed?
2. Does it actually reduce cache misses?

Whether it improves speed can easily be benchmarked.



(a) Compiler optimizations.
Optimized code.
Mean: 3.0708s

(b) Compiler optimizations.
Optimized and transposed code.
Mean: 2.1714s

Figure 8: Performance comparison between unoptimized code, optimized code and optimized code with compiler optimization enabled.

For finding out whether it reduces cache misses, we can use `iai`.

3.6 Iai

`Iai` [40] is a high-precision, one-shot benchmark framework for Rust code. One-shot means that the code is only run a single time. This is possible by leveraging `cachegrind` [36] under the hood to simulate the CPU and its caches, allowing us to count all cache accesses. Furthermore, it can be used for Continuous Integration (CI) pipelines since it solves the noisy-neighbour problem of multiple jobs executed on the same runner. Here are the results:

```

1  iai_normal
2  Instructions:      13970975862
3  L1 Accesses:      17192372607
4  L2 Accesses:      1074884737
5  RAM Accesses:      262191
6  Estimated Cycles:  22575972977
7
8  iai_transpose
9  Instructions:      9144912377
10 L1 Accesses:      12838193034
11 L2 Accesses:      68158189
12 RAM Accesses:      328137
13 Estimated Cycles:  13190468774

```

Listing 6: The results running `iai`

Here one can see that, although more RAM accesses, it has better L1 and L2 utilization.

4 A glimpse of (Inter-Node) Parallelism

Rust has many ways to do inter-node parallelism¹⁶. One can categorize inter-node parallelism into two categories: Single thread parallelism using SIMD instructions and multi threading. In this chapter, we will give a high-level overview how to achieve both.

4.1 SIMD

While a complete introduction in Single Instruction Multiple Data (SIMD) programming would be an report on its own¹⁷ it is noteworthy to say that Rust has two different approaches to support SIMD programming. The old, processor specific API and the new, portable SIMD API.

Processor specific API: The processor specific API is experimental only and classified as `unsafe`, i.e. it doesn't give any memory guarantees. It is composed of the direct low level intrinsics provided by the CPU manufacturer and has the same function definitions as the C API. The only reason is that it is part of the `core` instead of `std` library: This means, it does not expect any memory allocator nor any OS syscalls to work properly and can thus be used on bare metal.

Portable SIMD: The portable SIMD API is, while also experimental, memory safe. Instead of providing instructions for any CPU architecture, it is generalized on a bit level with types such as `std::simd::{f32x8, f64x4, i32x8}`. This makes it the preferred API for non-bare metal programming. It is part of the `std` library.

Lastly, note that code that does not have those processor features will produce undefined behaviour. There are two ways to mitigate this: If the target architecture is known at compile time, Rust supports conditional compilation^{18,19} to provide alternatives to architecture specific code. If this is not the case, functions such as `std::is_x86_feature_detected` can be used. Note that these should not be used in hot loops as they provide a runtime overhead.

4.2 Multithreading

Rust supports several ways of doing multi threading. First of all, the standard library offers many primitives around simple OS-threads²⁰ See the “Fearless Concurrency” chapter of the Rust book for an introduction [45].

¹⁶Rust also support intra-node parallelism using `rsmpi` [42], a rust-native MPI library compatible with OpenMPI and MPICH. Unfortunately, this is out of scope here. For more information, see my report on walky [43], the rusty TSP solver.

¹⁷For a great introduction on how to do SIMD in Rust, see the SIMD Rust on Android Talk by Guillaume Endignoux [44].

¹⁸Compile for specific architecture: `#[cfg(target_arch="x86_64")]`

¹⁹Compile for specific feature: `#[cfg(target_feature="aes")]`

²⁰Rust also supported green threads before 1.0 but they were cut because the scheduling meant that they were not zero cost.

Furthermore, Rust provides an `async/await` pattern for managing async Input / Output (I/O). In order to enable the usage in many, vastly different environments such as Internet of Things (IoT), Rust requires the developer to bring their own async runtime. Most projects use `Tokio` [46], although other projects such as the simpler `smol` or `fuchsia-async` [47] used in Google's Fuchsia. For more information to `async/await`, see the official async book [48], the announcement talk from WithoutBoats [49] or `fasterthanlimes` "Understanding Rust futures by going way too deep" [50].

Lastly, there are several utility libraries. Here, we will focus on `rayon` because of its simplicity.

4.2.1 Rayon

Rayon is a high-level parallelism library using dynamically sized thread pools. It guarantees **data-race freedom** by allowing only one thread to write at a time. Its main features are drop-in parallel iterators: By replacing `.iter()` with `.par_iter`, it is possible to use all functions provided for iterators, such as `.map()`, `.filter()`, `.reduce()` for typical functional patterns or `.join(|| a(), || b())` enabling the fork-join computation model. It is best explained with a code example. Let's rewrite our function in a more iterator based version:

```

1 fn matmul3(a: &[f32], b: &[f32], result: &mut [f32], n: usize) {
2     result.iter_mut().enumerate().for_each(|(idx, res)| {
3         let i = idx / n;
4         let j = idx % n;
5         *res = (0..n).map(|k| a[i * n + k] * b[k * n + j]).sum();
6     });
7 }

```

Listing 7: An more functional version of our matrix multiplication

This can be parallelized by only replacing `.iter_mut()` with `.par_iter_mut()`:

```

1 fn matmul3(a: &[f32], b: &[f32], result: &mut [f32], n: usize) {
2     result.par_iter_mut().enumerate().for_each(|(idx, res)| {
3         let i = idx / n;
4         let j = idx % n;
5         *res = (0..n).map(|k| a[i * n + k] * b[k * n + j]).sum();
6     });
7 }

```

Listing 8: This is the parallelized version, changing a single function call!

5 Conclusion and Further Ressources

To conclude, although many parts are still experimental, all tooling for proper performance engineering exists, making Rust a viable programming language for HPC. A summary of all tools can be found in the appendix.

If one is more interested in performance engineering, the best resources for understanding performance tuning in Rust is the “Rust Performance Book” [51]. To understand more about performance engineering and the theory behind it, the free online book “Algorithmica: Algorithms for Modern Hardware” [52] is a good starting point. Finally, if one is more interested in intra-node parallelism, the `rsmpi` library [42] has great examples to get started.

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A Work sharing

If you worked in a group, describe here how you distributed the work and the actual contributions of each peer.

A.1 Hans

...

A.2 Peter

...

B Code samples

This is part of the appendix...