

# JIT (Just-In-Time) Compilation

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2025-02-13

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## Introduction

This document is an extension of Notes 5 and 6 and will focus on how you can help the JIT compiler optimize your code.

We talked before about how Julia runs code as illustrated in the following flowchart:



```
y = 1
y = 2
x = y
```

A human can easily see that the first assignment to `y` is not needed, but it is more complicated for a machine. In SSA form, the code would look like this:

```
y1 = 1
y2 = 2
x1 = y2
```

In this form, it is clear that the first assignment to `y` is not needed, since `y1` is never used.

From the [manual](#):

Julia uses a static single assignment intermediate representation (SSA IR) to perform optimization. This IR is different from LLVM IR, and unique to Julia. It allows for Julia specific optimizations.

1. Basic blocks (regions with no control flow) are explicitly annotated.
2. `if/else` and loops are turned into `goto` statements.
3. lines with multiple operations are split into multiple lines by introducing variables.

```
function foo(x)
    y = sin(x)
    if x > 5.0
        y = y + cos(x)
    end
    return exp(2) + y
end;

using InteractiveUtils
@code_typed foo(1.0)
```

```
CodeInfo(
1  %1 = invoke Main.sin(x::Float64)::Float64
   %2 = Base.lt_float(5.0, x)::Bool
   goto #3 if not %2
2  %4 = invoke Main.cos(x::Float64)::Float64
   %5 = Base.add_float(%1, %4)::Float64
3  %6 = (#2 => %5, #1 => %1)::Float64
   %7 = Base.add_float(7.38905609893065, %6)::Float64
   return %7
) => Float64
```

There are four different categories of IR “nodes” that get generated from the AST, and allow for a Julia-specific [SSA-IR data structure](#).

## Optimization passes

The optimization pipeline is a complicated process that involves many steps and can be read about in detail [here](#). The main steps are:

1. **Early Simplification**
  - a. Simplify IR. Branch prediction hints, simplify control flow, dead code elimination, ...
2. **Early Optimization**
  - a. Reduce number of instructions. Common subexpression elimination, ...
3. **Loop Optimization**
  - a. Canonicalize and simplify loops. Loop fusion, loop unrolling, loop interchange, ...
4. **Scalar Optimization**
  - a. More expensive optimization passes. Global value numbering, proving branches never taken, ...
5. **Vectorization**
  - a. Vectorize. Earlier passes make this easier and reduce overhead in this step.
6. **Intrinsic Lowering**
  - a. Custom intrinsics. Exception handling, garbage collection, ...
7. **Cleanup**
  - a. Last-chance small optimizations. Fused multiply-add, ...

## Examples

Here are some examples of the techniques the optimization pipeline employs. There are many, many more, but these are some of the common ones as mentioned in the Julia docs:

1. **Dead code elimination (DCE)**: This optimization pass removes code that is never executed.
  - a. The conditional block is never executed, so the code inside can be removed:

```
function foo(x)
    if false
        x += 1
    end
    return x
end
```

2. **Constant propagation**: This optimization pass replaces variables with their constant values.
  - a. The following function can be simplified to `return 5`:

```
function foo(x)
    x = 3
    y = 2
    return x + y
end
```

3. **Common subexpression elimination (CSE)**: This optimization pass eliminates redundant computations.
  - a. The following function may be compiled to store the value of `x^2` in a temporary variable and reuse it:

```
function foo(x)
    return x^2 + x^2 + x^2 + x^2
end
```

4. **Loop unrolling:** Loops traditionally have a condition that needs to be checked at every iteration. If the number of iterations is known at compile time, the loop can be unrolled to remove the condition check.

- a. The following loop may be unrolled to remove the condition check:

```
a = 0
for i in 1:4
    a += i
end
```

```
a = 0
a += 1
a += 2
a += 3
a += 4
```

5. **Loop fusion:** This optimization pass combines multiple loops into one to reduce the number of iterations.

- a. The following two loops may be fused into one:

```
a = 0
b = 0
for i in 1:4
    a += i
end
for j in 1:4
    b += j
end
```

```
a = 0
b = 0
for i in 1:4
    a += i
    b += j
end
```

6. **Loop interchange:** This optimization pass changes the order of nested loops to improve cache performance.

- a. The following nested loops may be interchanged to improve cache performance:

```
for i in 1:4
    for j in 1:4
        a[i, j] = i + j
    end
end
```

```

for j in 1:4
    for i in 1:4
        a[i, j] = i + j
    end
end

```

7. **Global value numbering (GVN)**: This optimization pass assigns a unique number to each value computed by the program and replaces the value with its number.

- a. After GVN, the following code can likely be optimized further by CSE (x and z can be replaced with w and y everywhere):

```

w = 3
x = 3
y = x + 4
z = w + 4

```

```

w := 3
x := w
y := w + 4
z := y

```

8. **Fused multiply-add (FMA)**: This optimization combines multiplication and addition instruction into a single instruction if the hardware supports it.

- a. The following code may be compiled to use an FMA instruction:

```

mul r1, r2, r3; multiply r2 and r3 and store in r1
add r4, r1, r5; add r1 and r5 and store in r4

```

```

; this process is done in a single instruction
fmadd r4, r2, r3, r5; multiply r2 and r3, add r5, and store in r4

```

## Techniques to help the JIT compiler

We talked last week about some techniques you can use to help the JIT compiler optimize your code, such as putting performance-critical code inside functions, avoiding global variables, typing your variables, and using the `const` keyword. Here are some more techniques, and you can read about many more in detail [here](#):

There are many good tips recommended by the manual, but here are a few that I think are quite useful or surprising. Most of these boil down to type stability:

### Write type-stable code

This code looks innocuous enough, but there is something wrong with it:

```

pos(x) = x < 0 ? 0 : x;

# This is equivalent to
function pos(x)
    if x < 0

```

```

        return 0
    else
        return x
    end
end;

```

0 is an integer, but `x` can be any type. This function is not type-stable because the return type depends on the input type. One may use the `zero` function to make this type-stable:

```

pos(x) = x < zero(x) ? zero(x) : x;

```

Similar functions exist for `oneunit`, `typemin`, and `typemax`.

A similar type-stability issue may also arise when using operations that may change the type of a variable such as `/`:

```

function foo(n)
    x = 1
    for i = 1:n
        x /= rand()
    end
    return x
end;

```

The manual outlines several possible fixes:

- Initialize `x` with `x = 1.0`
- Declare the type of `x` explicitly as `x::Float64 = 1`
- Use an explicit conversion by `x = oneunit(Float64)`
- Initialize with the first loop iteration, to `x = 1 / rand()`, then loop for `i = 2:10`

Be wary of memory allocations

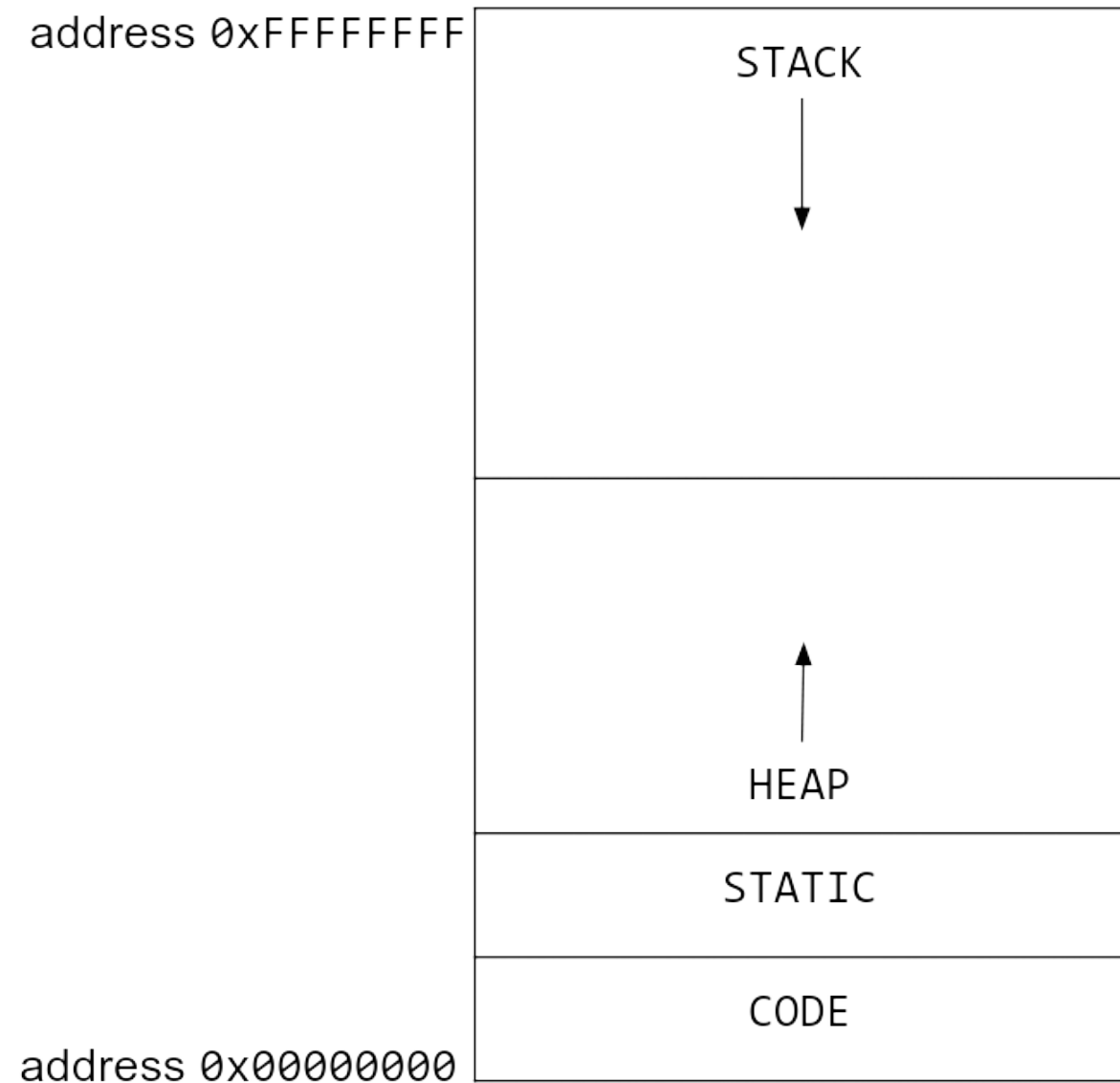


Figure 2: Memory allocation diagram from CS61C

Heap memory allocation can be a bottleneck in your code. If you are allocating memory in a loop, you may be slowing down your code. Here is a toy code segment that repeatedly allocates memory:

```
function xinc(x)
    return [x, x+1, x+2]
```



```

end;

function loopinc()
    y = 0
    for i = 1:10^7
        ret = xinc(i)
        y += ret[2]
    end
    return y
end;

```

This code, while unrealistic, is a good example of how memory allocation can slow down your code. The `xinc` function allocates memory every time it is called, and the `loopinc` function calls `xinc` several times. This code can be optimized by preallocating memory:

```

function xinc!(ret, x)
    ret[1] = x
    ret[2] = x+1
    ret[3] = x+2
end;

function loopinc_prealloc()
    y = 0
    ret = [0, 0, 0]
    for i = 1:10^7
        xinc!(ret, i)
        y += ret[2]
    end
    return y
end;

```

```
@time loopinc()
```

```

0.392091 seconds (10.00 M allocations: 762.939 MiB, 8.07% gc time)
50000015000000

```

```
@time loopinc_prealloc()
```

```

0.003303 seconds (1 allocation: 80 bytes)
50000015000000

```

**Be wary of memory allocations, again**

```

x = rand(1000);
function sum_global()
    s = 0.0

```

```

    for i in x
        s += i
    end
    return s
end;
@time sum_global()

```

0.010335 seconds (3.68 k allocations: 78.109 KiB, 97.79% compilation time)

501.4832321669699

```

function sum_local()
    s = 0.0
    x = rand(1000)
    for i in x
        s += i
    end
    return s
end;
@time sum_local()

```

0.000016 seconds (1 allocation: 7.938 KiB)

496.83331006478454

The global nature of `x` prevents the compiler from making many optimizations, especially since it is not typed. Because it is global, and `x` needs to persist, it requires heap memory allocation. The local version of `x` is typed and stack-allocated, which allows the compiler to optimize the code better. Stack allocation is usually much faster than heap allocation.

## Function barriers

Try to separate functionality into different functions as much as possible. Often there is some setup, work, and cleanup to be done - it is a good idea to separate these into different functions. This will help with compiler optimizations, but it often makes the code more readable and reusable.

Consider the following (strange) code. `a` will be an array of `Int64`s or `Float64`s, depending on the random value, but it can only be determined at runtime. Though this is a contrived example, sometimes there are legitimate cases where things cannot be determined until runtime.

```

function strange_twos(n)
    a = Vector{rand{Bool} ? Int64 : Float64}(undef, n)
    for i = 1:n
        a[i] = 2
    end
    return a
end;
@time strange_twos(10^6)

```

0.067537 seconds (999.54 k allocations: 22.883 MiB, 9.98% gc time, 11.23% compilation time)

1000000-element Vector{Float64}:

2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0

2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0  
2.0

Instead, separating out the type determination into a different function can help the compiler:

```
function fill_twos!(a)
    for i = eachindex(a)
        a[i] = 2
    end
end;

function strange_twos_better(n)
    a = Vector{rand(Bool) ? Int64 : Float64}(undef, n)
    fill_twos!(a)
    return a
end;

@time strange_twos_better(10^6)
```

0.016466 seconds (1.88 k allocations: 7.752 MiB, 85.50% compilation time)

1000000-element Vector{Int64}:

2  
2  
2  
2  
2  
2  
2  
2

```

2
2
2

2
2
2
2
2
2
2
2
2
2
2

```

### LoopVectorization.@turbo

Here is some Julia code for a naive matrix multiplication algorithm:

```

function AmulB!(C, A, B)
    for m in axes(A, 1), n in axes(B, 2)
        C = zero(eltype(C)) # element type
        for k in axes(A, 2)
            C += A[m,k] * B[k,n]
        end
        C[m,n] = C
    end
end;

@time AmulB!(rand(1000,1000), rand(1000,1000), rand(1000,1000))

```

1.551943 seconds (6 allocations: 22.888 MiB, 0.35% gc time)

The [LoopVectorization.jl](#) package offers the `@turbo` macro, which optimizes loops using memory-efficient SIMD (vectorized) instructions. However, one can only apply this to loops that meet certain conditions as outlined in the package [README](#).

```

using LoopVectorization;

function AmulB_turbo!(C, A, B)
    @turbo for m in indices((A,C), 1), n in indices((B,C), 2) # indices((A,C),1) == axes(A,1) == axes(C,1)
        C = zero(eltype(C))
        for k in indices((A,B), (2,1)) # indices((A,B), (2,1)) == axes(A,2) == axes(B,1)
            C += A[m,k] * B[k,n]
        end
        C[m,n] = C
    end
end;

```

```
@time AmulB_turbo!(rand(1000,1000), rand(1000,1000), rand(1000,1000))
```

0.278815 seconds (6 allocations: 22.888 MiB, 29.74% gc time)

For comparison, here is BLAS matrix multiplication:

```
using LinearAlgebra;  
BLAS.set_num_threads(1);
```

```
function BLAS_mul(C, A, B)  
    BLAS.gemm!('N', 'N', 1.0, A, B, 0.0, C)  
end;
```

```
@time BLAS_mul(rand(1000,1000), rand(1000,1000), rand(1000,1000))
```

0.054331 seconds (6 allocations: 22.888 MiB)

1000×1000 Matrix{Float64}:

248.336	257.609	248.08	256.299	...	260.25	259.746	245.641	260.788
235.332	245.5	240.357	241.355		248.488	248.664	242.354	245.066
246.594	254.846	247.56	251.96		255.373	263.292	245.485	254.569
248.581	258.248	251.493	251.887		259.748	263.35	246.862	260.73
240.18	252.708	241.659	245.944		254.413	254.278	245.656	251.56
255.512	261.387	250.138	259.998	...	260.362	263.559	252.572	260.347
236.633	243.919	236.093	248.823		249.412	253.846	239.416	247.574
235.795	244.992	236.674	243.36		244.352	250.957	238.958	246.798
248.289	259.94	250.205	256.818		257.064	268.452	247.938	259.163
244.051	244.801	242.798	245.431		251.302	252.892	239.189	250.295
244.251	249.391	245.1	249.481		253.467	253.693	239.62	249.798
241.601	243.996	236.219	242.08		248.673	247.771	240.645	248.227
231.72	240.715	233.607	236.33		242.289	240.517	233.194	240.22
242.062	251.34	243.808	250.083		254.644	263.435	248.02	248.828
237.201	248.165	234.027	238.163	...	239.677	245.218	236.722	243.229
238.149	250.081	242.184	247.236		250.085	249.504	240.873	248.561
244.917	253.121	246.216	254.414		257.726	262.651	250.729	256.835
252.353	264.778	256.772	263.403		267.757	271.093	254.141	263.334
247.983	255.636	242.911	250.991		254.755	259.298	243.792	257.76