

Modular



Mojo GPU Compilation 🔥

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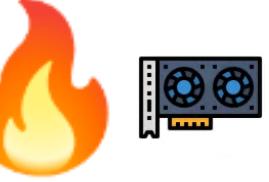
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LLVM Developers' Meeting 2025

GPU Programming in Mojo



- Pythonic **systems programming** language
 - Generic programming, type system, and memory safety
 - Blazing fast
 - Best way to extend Python to CPUs and GPUs
 - Bedrock for Modular's MAX inference engine.
- **Unified programming** for CPU + GPU
 - The full power of standard CUDA/ROCM, but without "CUDA"
 - Threads, warps, sync primitives, WMMA instructions
 - Generate executables **without** using vendor toolkits or libraries
 - All GPU kernels for Nvidia, AMD, Apple written in Mojo
- **Library driven** with **simple** compiler support

```

from math import ceildiv
from sys import has_accelerator
from gpu import global_idx
from gpu.host import DeviceContext
from layout import Layout, LayoutTensor

alias float_dtype = Dtype.float32
alias VECTOR_WIDTH = 10
alias BLOCK_SIZE = 5
alias layout = Layout.row_major(VECTOR_WIDTH)

fn vector_addition(
    lhs_tensor: LayoutTensor[float_dtype, layout, MutableAnyOrigin],
    rhs_tensor: LayoutTensor[float_dtype, layout, MutableAnyOrigin],
    out_tensor: LayoutTensor[float_dtype, layout, MutableAnyOrigin],
    size: Int,
):
    """The calculation to perform across the vector on the GPU."""
    var global_tid = global_idx.x
    if global_tid < UInt(size):
        out_tensor[global_tid] = lhs_tensor[global_tid] + rhs_tensor[global_tid]

def main():
    constrained[has_accelerator(), "This example requires a supported GPU"]()

    # Get context for the attached GPU
    var ctx = DeviceContext()

    # Allocate data on the GPU address space
    var lhs_buffer = ctx.enqueue_create_buffer[float_dtype](VECTOR_WIDTH)
    var rhs_buffer = ctx.enqueue_create_buffer[float_dtype](VECTOR_WIDTH)
    var out_buffer = ctx.enqueue_create_buffer[float_dtype](VECTOR_WIDTH)

    # Fill in values across the entire width
    _ = lhs_buffer.enqueue_fill(1.25)
    _ = rhs_buffer.enqueue_fill(2.5)

    # Wrap the device buffers in tensors
    var lhs_tensor = LayoutTensor[float_dtype, layout](lhs_buffer)
    var rhs_tensor = LayoutTensor[float_dtype, layout](rhs_buffer)
    var out_tensor = LayoutTensor[float_dtype, layout](out_buffer)

    # Calculate the number of blocks needed to cover the vector
    var grid_dim = ceildiv(VECTOR_WIDTH, BLOCK_SIZE)

    # Launch the vector_addition function as a GPU kernel
    ctx.enqueue_function_checked[vector_addition, vector_addition](
        lhs_tensor,
        rhs_tensor,
        out_tensor,
        VECTOR_WIDTH,
        grid_dim=grid_dim,
        block_dim=BLOCK_SIZE,
    )

    # Map to host so that values can be printed from the CPU
    with out_buffer.map_to_host() as host_buffer:
        var host_tensor = LayoutTensor[float_dtype, layout](host_buffer)
        print("Resulting vector:", host_tensor)

```

Annotations:

- GPU kernel**: Points to the `vector_addition` function.
- CPU driver code**: Points to the `main` function.
- GPU device context**: Points to the `DeviceContext()` call.
- GPU buffers**: Points to the `lhs_buffer`, `rhs_buffer`, and `out_buffer` declarations.
- compile and launch GPU kernel**: Points to the `ctx.enqueue_function_checked` call.
- device buffer to host**: Points to the `map_to_host` method and the `print` statement.

Mojo GPU Compilation Flow

```
def main():
    constrained[has_accelerator(), "This example requires a supported GPU"]()

    # Get context for the attached GPU
    var ctx = DeviceContext()

    # Allocate data on the GPU address space
    var lhs_buffer = ctx.enqueue_create_buffer[float_dtype](VECTOR_WIDTH)
    var rhs_buffer = ctx.enqueue_create_buffer[float_dtype](VECTOR_WIDTH)
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    # Fill in values across the entire width
    _ = lhs_buffer.enqueue_fill(1.25)
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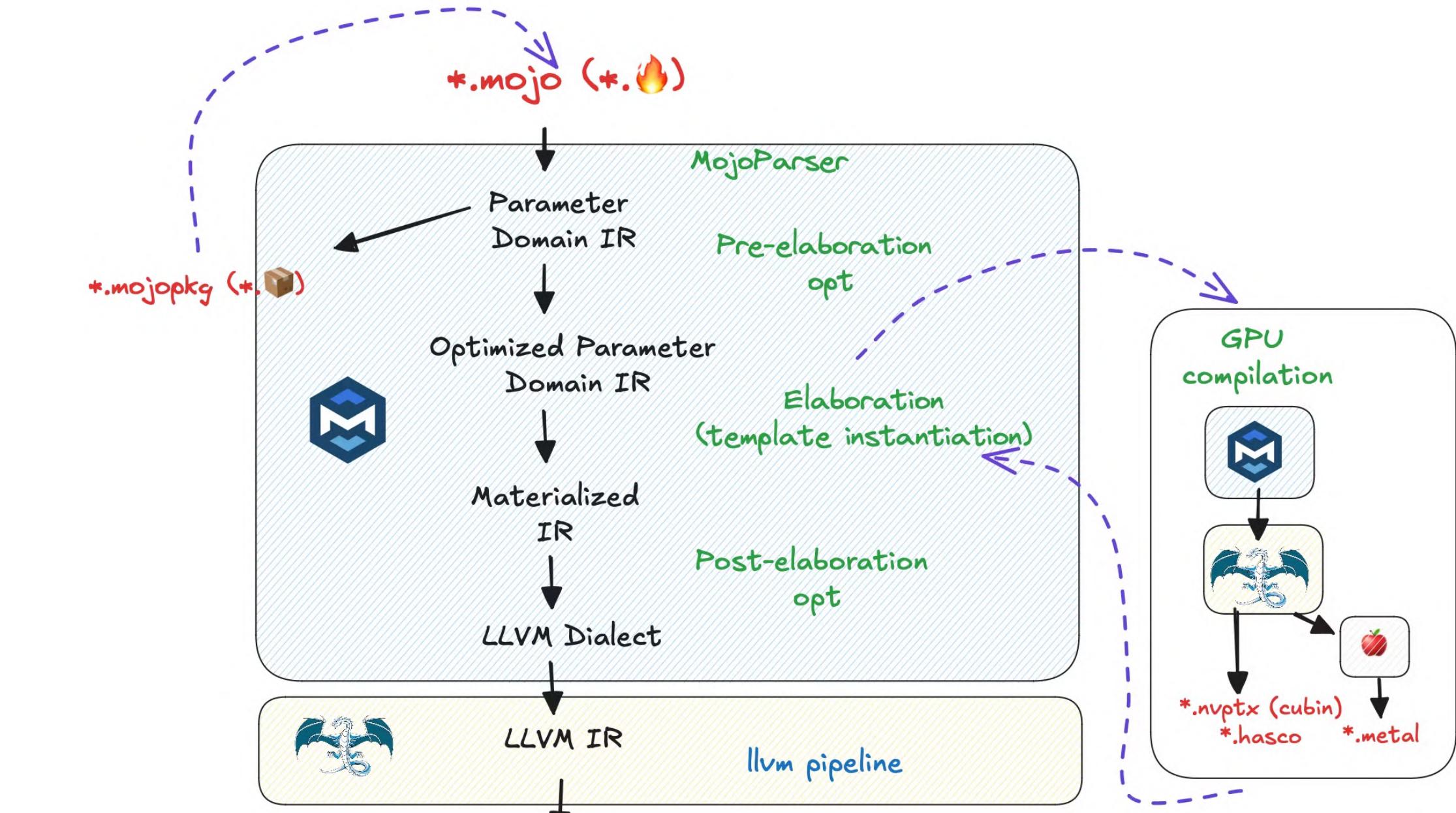
    # Wrap the device buffers in tensors
    var lhs_tensor = LayoutTensor[float_dtype, layout](lhs_buffer)
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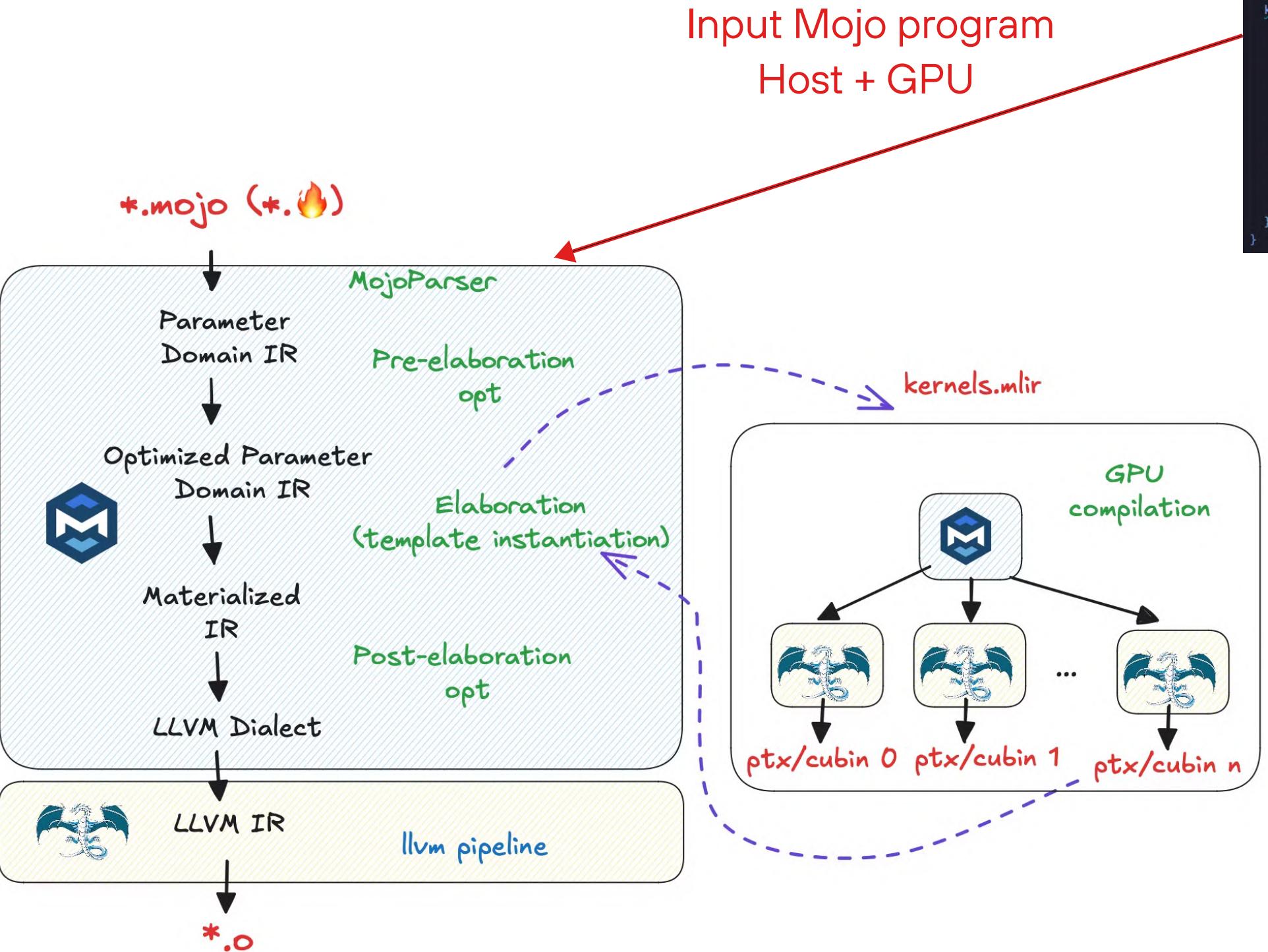
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    ctx.enqueue_function_checked[vector_addition, vector_addition](
        lhs_tensor,
        rhs_tensor,
        out_tensor,
        VECTOR_WIDTH,
        grid_dim=grid_dim,
        block_dim=BLOCK_SIZE,
    )

    # Map to host so that values can be printed from the CPU
    with out_buffer.map_to_host() as host_buffer:
        var host_tensor = LayoutTensor[float_dtype, layout](host_buffer)
        print("Resulting vector:", host_tensor)
```

GPU entry
function as a
parameter

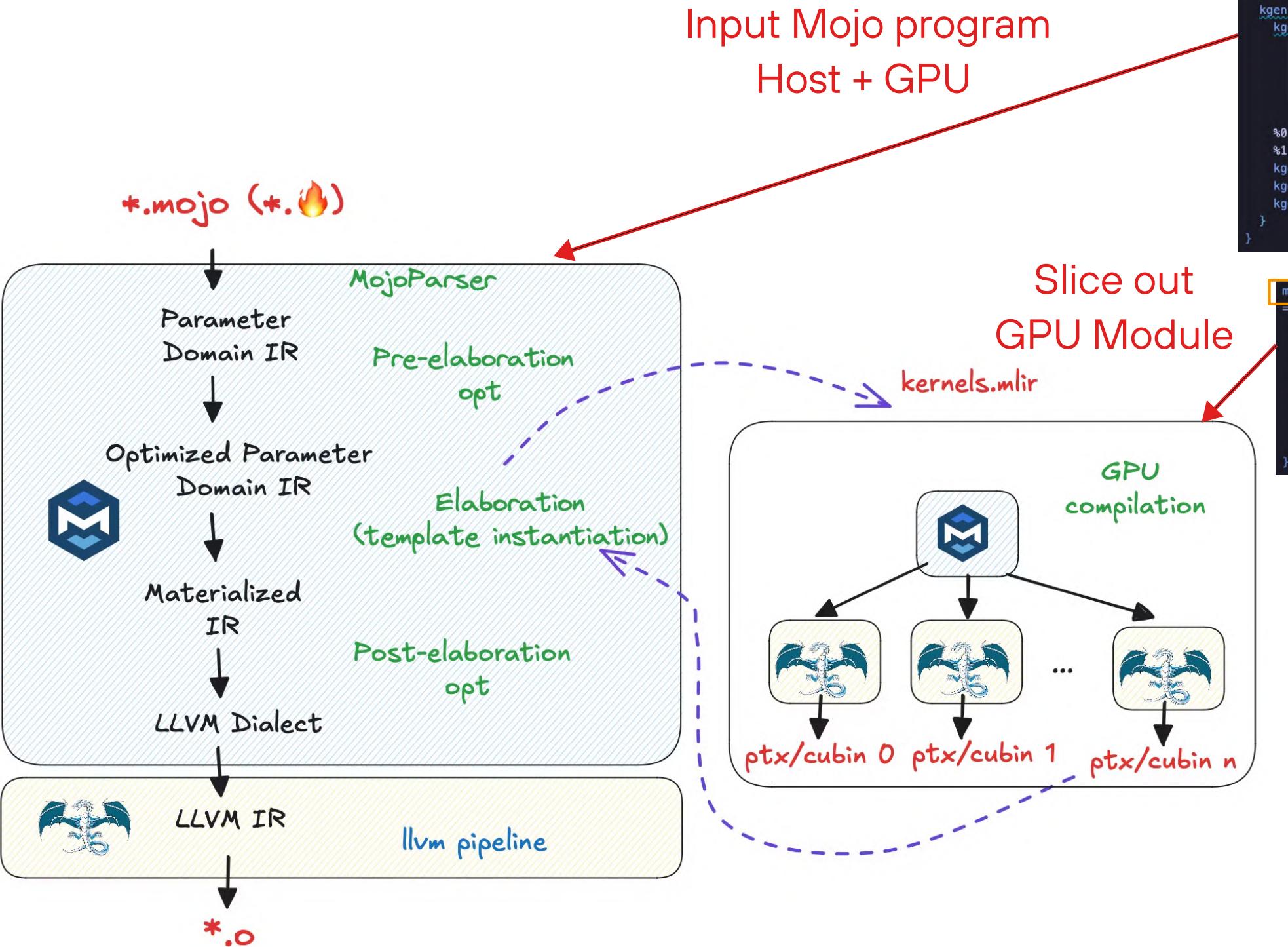


Mojo GPU Compilation Flow



```
module_attributes {M.target_info = #M.target<triple = "arm64-apple-darwin23.6.0", arch = "apple-m2", features = "+aes,+bf16,+complxnum,+crc,+dotprod,+fp-armv8,+fp16mlt,+fpac,+fullfp16,+l8mm,+lscconv,+lse,+neon,+pauth,+permon,+ras,+rcc,+rum,+sna2,+sha3,+ssbs", data_layout = "e-m:o-p270:32:32-p271:32:32-p272:64:64-i64:64-i128:128-32:64-S128-Fn32", relocation_model = "pic", simd_bit_width = 128, index_bit_width = 64>, kgen_env = #kgen_env<{}>} {
    kgen.generator @kernel1() -> !kgen.none {
        %none = kgen.param.constant none = <#kgen.none>
        kgen.return %none : !kgen.none
    }
    kgen.generator @kernel2() -> !kgen.none {
        %none = kgen.param.constant none = <#kgen.none>
        kgen.return %none : !kgen.none
    }
    kgen.generator export @entry(%arg0: !kgen.pointer<none>) {
        kgen.param.declare nvptx: target = <#kgen.target<triple = "nvptx64-nvidia-cuda", arch = "sm_80", simd_bit_width = 128, index_bit_width = 64, tune_cpu = "sm_80">>
        %0:2 = kgen.compile_offload<nvptx, 0, "", :() -> !kgen.none @kernel1> -> string, index
        %1:2 = kgen.compile_offload<nvptx, 0, "", :() -> !kgen.none @kernel2> -> string, index
        kgen.call @launch_kernel(%0#0, %0#1) : (!kgen.string, index) -> !kgen.none
        kgen.call @launch_kernel(%1#0, %1#1) : (!kgen.string, index) -> !kgen.none
        kgen.return
    }
}
```

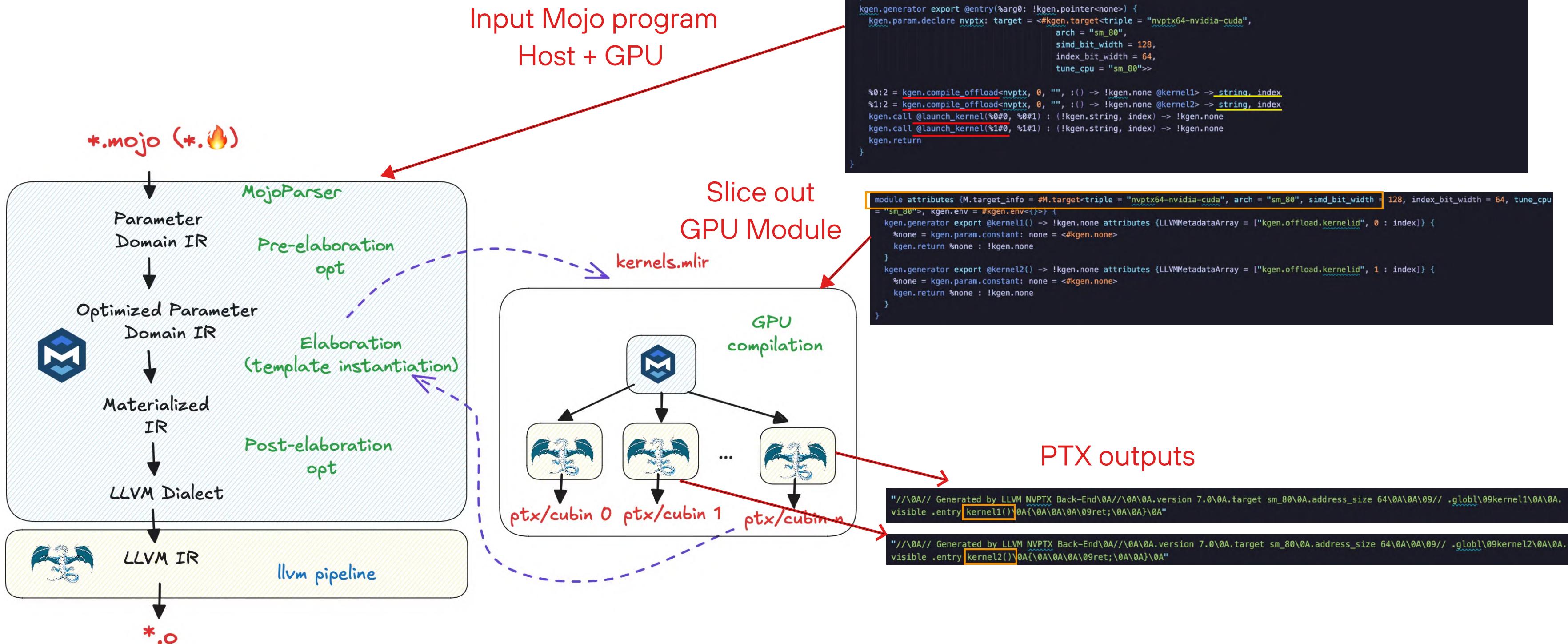
Mojo GPU Compilation Flow



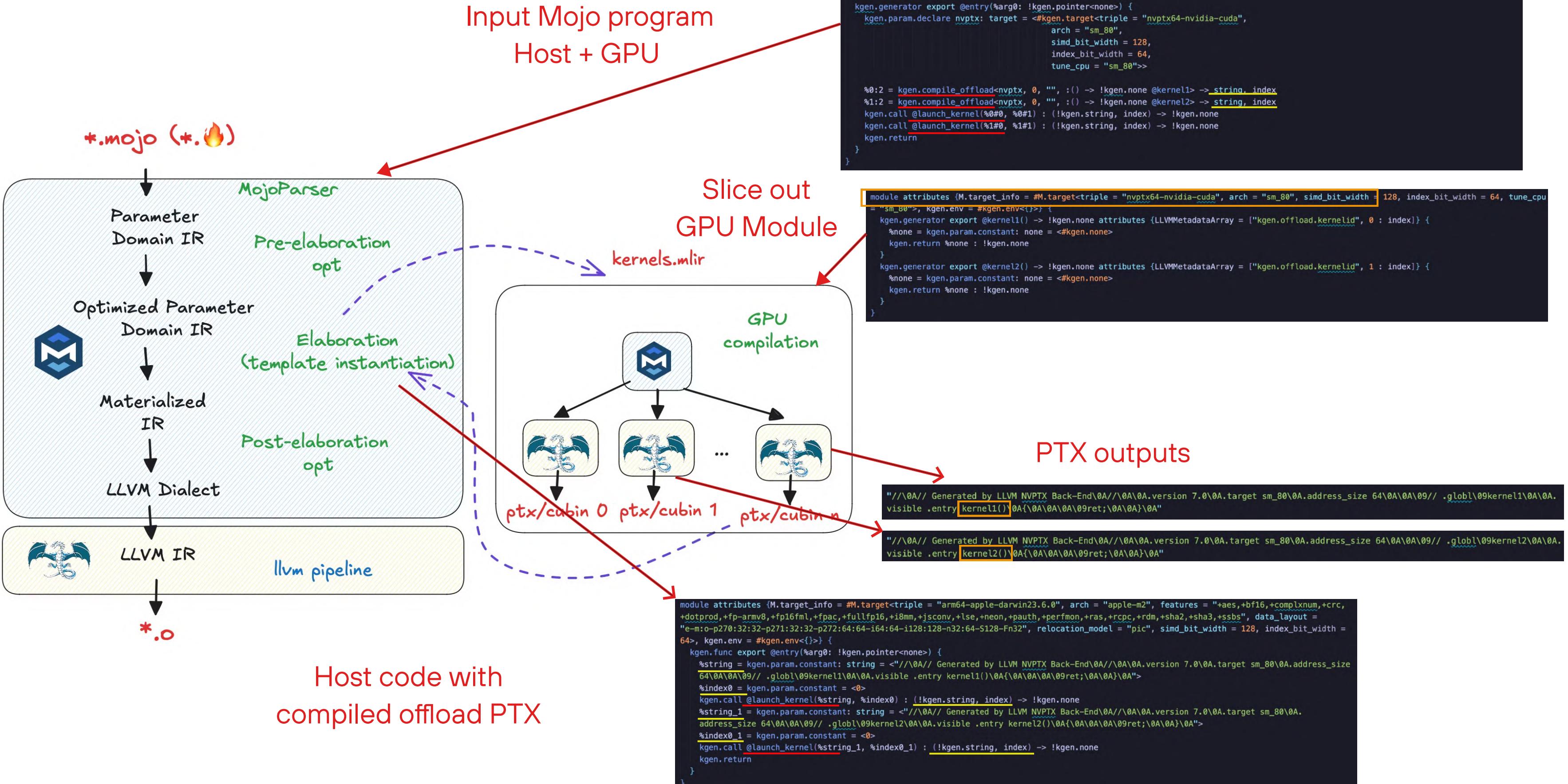
```
module attributes {M.target_info = #M.target<triple = "arm64-apple-darwin23.6.0", arch = "apple-m2", features = "+aes,+bf16,+complxnum,+crc,+dotprod,+fp-armv8,+fp16imm,+fpac,+fullfp16,+l18nm,+lscconv,+lse,+neon,+pauth,+perfmom,+ras,+riscv,+rum,+sna2,+sha3,+ssbs", data_layout = "e-m:0-p270:32:32-p271:32:32-p272:64:64-i64:i128:i128-32:64-S128-Fn32", relocation_model = "pic", simd_bit_width = 128, index_bit_width = 64>, kgen.env = #kgen.env<{}>} {
    kgen.generator @kernel1() -> !kgen.none {
        %none = kgen.param.constant: none = <#kgen.none>
        kgen.return %none : !kgen.none
    }
    kgen.generator @kernel2() -> !kgen.none {
        %none = kgen.param.constant: none = <#kgen.none>
        kgen.return %none : !kgen.none
    }
    kgen.generator export @entry(%arg0: !kgen.pointer<none>) {
        kgen.param.declare nvptx: target = <kgen.target<triple = "nvptx64-nvidia-cuda", arch = "sm_80", simd_bit_width = 128, index_bit_width = 64, tune_cpu = "sm_80">>
        %0:2 = kgen.compile_offload<nvptx, 0, "", :() -> !kgen.none @kernel1> -> string, index
        %1:2 = kgen.compile_offload<nvptx, 0, "", :() -> !kgen.none @kernel2> -> string, index
        kgen.call @launch_kernel(%0#0, %0#1) : (!kgen.string, index) -> !kgen.none
        kgen.call @launch_kernel(%1#0, %1#1) : (!kgen.string, index) -> !kgen.none
        kgen.return
    }
}
```

```
module attributes {M.target_info = #M.target<triple = "nvptx64-nvidia-cuda", arch = "sm_80", simd_bit_width = 128, index_bit_width = 64, tune_cpu = "sm_80">, kgen.env = #kgen.env<{}>} {
    kgen.generator export @kernel1() -> !kgen.none attributes {LLVMMetadataArray = ["kgen.offload.kernelid", 0 : index]} {
        %none = kgen.param.constant: none = <#kgen.none>
        kgen.return %none : !kgen.none
    }
    kgen.generator export @kernel2() -> !kgen.none attributes {LLVMMetadataArray = ["kgen.offload.kernelid", 1 : index]} {
        %none = kgen.param.constant: none = <#kgen.none>
        kgen.return %none : !kgen.none
    }
}
```

Mojo GPU Compilation Flow

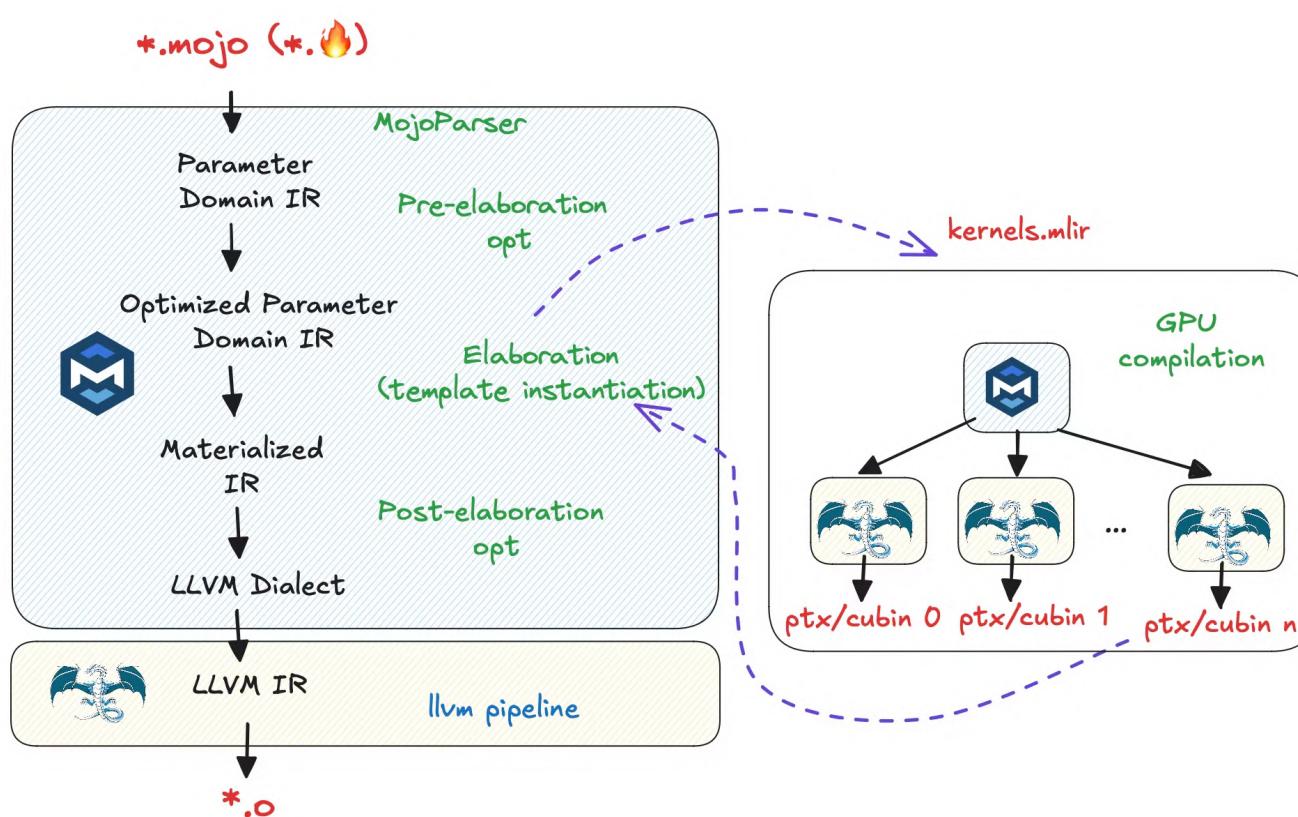


Mojo GPU Compilation Flow



Compiler support for Debugging Kernels

- Inspecting Mojo GPU kernel in LLVM IR, assembly (PTX), or object file (cubin, hsaco)
- Same GPU compilation flow, just change what the pipeline produces.
- Plug the result as string to host code.



The screenshot shows the LLVM pipeline interface. It displays three stages of LLVM IR:

- asm**: Assembly code generated by the LLVM NVPTX Back-End.
- llvm IR**: LLVM IR for the CUDA target.
- opt llvm IR**: LLVM IR optimized for the Apple M2 target.

Arrows from the host code on the right point to the corresponding LLVM IR stages, indicating where specific compiler options like emission_kind and LLVM dialect are applied.

```

@fieldwise_init
@register_passable("trivial")
struct _Info:
    var kernel: __mlir_type.`!kgen.string`
    var name: __mlir_type.`!kgen.string`
    var num_captures: __mlir_type.index

@fieldwise_init
@register_passable("trivial")
struct Info:
    var kernel: StaticString
    var name: StaticString
    var num_captures: Int

@always_inline
fn _compile_info[
    func_type: AnyTrivialRegType, //,
    func: func_type,
    ,
    emission_kind: StaticString = "asm",
    target: _TargetType = A100.target(),
    compile_options: StaticString = CompilationTarget[
        target
    ].default_compile_options(),
]() -> Info:
    var info = __mlir_op.`kgen.compile_offload`[
        target_type=target,
        emission_kind = _get_emission_kind_id[emission_kind]().__mlir_value,
        emission_option = _get_kgen_string[compile_options](),
        func=func,
        _type=_Info,
    }()
    return Info(
        StaticString(info.kernel),
        StaticString(info.name),
        Int(__mlir_value=info.num_captures),
    )

fn hello():
    pass

fn main():
    # compile kernel to asm.
    t1 = _compile_info[hello, emission_kind="asm"]()
    print(t1.kernel)

    # compile kernel to llvm ir.
    t2 = _compile_info[hello, emission_kind="llvm"]()
    print(t2.kernel)

    # compile kernel to optimized llvm ir.
    t3 = _compile_info[hello, emission_kind="llvm-opt"]()
    print(t3.kernel)
  
```

This host code demonstrates how to use the compiler's `_compile_info` function to generate LLVM IR for different targets and dialects. It shows examples for assembly, LLVM IR, and LLVM-opt IR, each with specific compiler options like `emission_kind` and `target`.

Conclusions

- Mojo provides a unified way to write CPU+GPU code => **one MLIR module**
- Library driven GPU feature implementation for different vendors => **simple compiler, no heroic magic**
- MLIR unlocks seamless compiler integration:
 - Native compiler support to know what to slice into GPU mlir modules during elaboration.
 - Add an mlir op kgen.compile_offload.
 - Mojo has support as MLIR sugar:
 - No need to change the parser to extend syntax.
 - Ease of writing library code that uses architecture specific dialects (nvvm, rocdl) and low-level intrinsics (llvm).
- Compiling multiple kernels in one MLIR module and split for LLVM pipeline => **fast compilation**
- **Generally applicable** to compile other accelerator offloads built on top of LLVM/MLIR framework.
- Mojo GPU kernels are all open-sourced

<https://github.com/modular/modular/tree/main/max/kernels>



**Thank you!
Hope to see you at the poster session!**

Acknowledgement:
The Mojo Language Team at Modular

