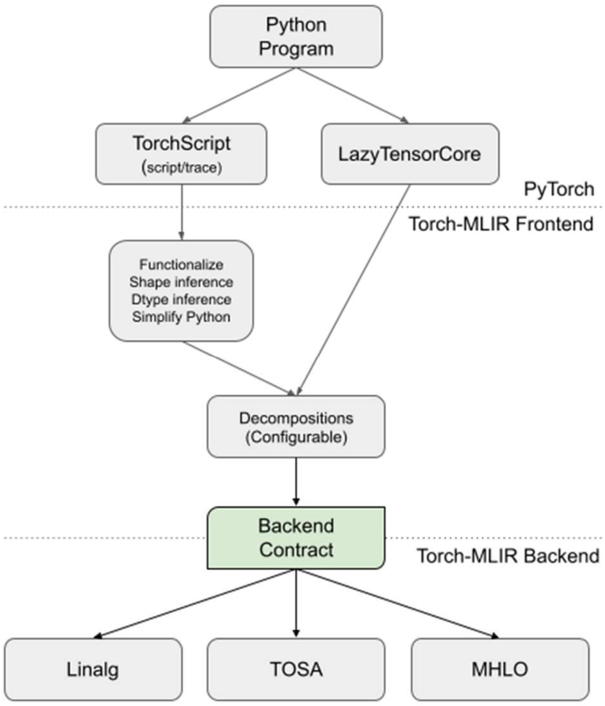
Torch-MLIR Architecture

Introduction

The Torch-MLIR project provides core infrastructure for bridging the PyTorch ecosystem and the MLIR ecosystem. For example, Torch-MLIR enables PyTorch models to be lowered to a few different MLIR dialects. Torch-MLIR does not attempt to provide a production end-to-end flow for PyTorch programs by itself, but is a useful component for constructing one.

Overview

Torch-MLIR has two parts, which we call the "frontend" and "backend". These two halves interface at an abstraction layer that we call the "backend contract", which is a subset of the torch dialect with certain properties appealing for backends to lower from.



The frontend of Torch-MLIR is concerned with interfacing to PyTorch itself, and then normalizing the program to the "backend contract". This part involves build system complexity and exposure to PyTorch APIs to get the program into the MLIR torch dialect. When we interface with TorchScript, we additionally have a large amount of lowering and simplification to do within MLIR on the torch dialect.

The "backend" of Torch-MLIR takes IR in the "backend contract" form and lowers it to various target dialects of interest to the MLIR ecosystem (various "backends"). In particular, right now we support lowering to:

- Linalg-on-Tensors (+ arith, tensor, etc.)
- TOSA
- StableHLO

The terms "frontend" and "backend" are highly overloaded in any compiler project, but frequently in Torch-MLIR this is the meaning that they have. Sometimes "frontend" can mean something even further up the stack, such as something in PyTorch itself. When there is ambiguity we will refer to this as "at the PyTorch level". Similarly, "backend" can sometimes refer to something sitting below Linalg-on-Tensors, TOSA, or StableHLO.

The torch dialect

See include/torch-mlir/Dialect/Torch/IR

The central MLIR abstraction in the Torch-MLIR project is the torch dialect. This dialect supports progressive lowering from the raw imported PyTorch programs that various PyTorch integration points provide, all the way down to the backend contract.

The torch dialect must be versatile enough to support being imported by any program capture mechanism in PyTorch -- this could be TorchDynamo, torch.fx, LazyTensorCore, TorchScript, torch.jit.trace, etc. Thankfully, PyTorch is factored such that we can handle this with one core import path, which is through the PyTorch "JIT IR", and lives in torch-mlir/python/torch_mlir/jit_ir_importer. The JIT IR is a highly principled IR that faithfully models a Python subset (+ tensors, the PyTorch op registry, and a few other things). All the other PyTorch program representations can eventually bottom-out on the JIT IR via some path provided by PyTorch. The torch dialect is almost entirely in 1:1 correspondence with the JIT IR -- this allows the importer to be extremely small (the core is under 500 lines of code).

Ops

See TorchOps.td

The ops in the torch dialect are almost entirely generated based on the PyTorch JIT IR operator registry via the script torch_ods_gen.py (invoked via update_torch_ods.sh). This script queries the registry and generates MLIR ODS in GeneratedTorchOps.td. We have a guide for adding a new op end-to-end.

There are also some manually implemented ops in the following categories (see TorchOps.td):

- Ops used for modeling PyTorch IValue object graphs (e.g. torch.nn_module, torch.class_type).
- torch.global_slot and related ops which are used to model an incremental lowering of the IValue object graphs.
- Ops that are supported in the JIT interpreter directly, and so don't have a corresponding op in the registry (e.g. torch.prim.If, torch.prim.ListConstruct, torch.constant.*)
- torch.operator which is used to represent ops from the registry which haven't been generated by torch_ods_gen.py.

Types

See TorchTypes.td

The torch dialect has a complete set of types modeling the PyTorch type system, which itself is a strongly typed subset of the Python type system (+ tensors). These types are almost all 1:1 with the corresponding PyTorch types.

The one exception where a significant amount of design work has been done in Torch-MLIR is the handling of tensors. Torch-MLIR's tensor types allow progressive lowering from raw imported IR which maybe be missing shapes, dtypes, and value semantics, into the backend contract which provides those. Torch-MLIR has two tensor types ValueTensorType (!torch.vtensor) and NonValueTensorType (!torch.tensor) sharing most of their definition in TorchTypes.td. The NonValueTensorType models a torch.Tensor including mutation, aliasing, etc. while the ValueTensorType has value semantics. That is, ValueTensorType is immutable and non-aliased. These types have a common C++ base class BaseTensorType which permits abstracting across them. Both ValueTensorType and NonValueTensorType have an optional list of optional sizes and an optional dtype.

The "backend contract"

See satisfiesBackendContract

The backend contract is a normalized form of the torch dialect with a set of properties that make it easy to lower into various forms such as Linalg-on-Tensors, TOSA, StableHLO, or other forms that we don't provide out of the box. The primary guarantees that we provide Torch-MLIR's backends are:

- All tensors have been converted to value semantics.
- All tensors have at least a known number of dimensions (i.e. rank), and ideally also have a precise size for each dimension.
- All tensors have a known dtype.
- Certain ops have been decomposed to make them easier to handle (this is configurable).

See the extensive comments in the function satisfiesBackendContract (and its callees) in the LowerToBackendContract pass for an extended rationale for these decisions, and a precise definition of the backend contract.

The Frontends

Torch-MLIR provides 2 main frontends:

- LazyTensorCore - a frontend that is based around intercepting PyTorch dispatcher calls and creating a graph that is lazily evaluated on demand.
- TorchScript - a frontend based around importing TorchScript functions or modules. Such modules or functions can be obtained via torch.jit.script, torch.jit.trace, or a few other methods in the PyTorch ecosystem.

Internally these share a lot of the core import code.

LazyTensorCore

Docs: https://github.com/llvm/torch-mlir/blob/main/docs/ltc_backend.md

LazyTensorCore (LTC) is a program capture method provided by PyTorch that does device-level tracing. This low-level interception point sits below gradient calculations, and is thus a good choice for training flows. The downside of LTC is that it depends on having the whole PyTorch runtime available, so cannot be used for ahead-of-time compilation or capturing standalone program artifacts.

From an implementation perspective, the JIT IR that is produced by LazyTensorCore has already had a number of transformations performed on it, in particular, after importing from JIT IR to MLIR, the backend contract is trivially satisfied. So the Torch-MLIR implementation complexity for LazyTensorCore is restricted to build system and PyTorch integration, rather than actual MLIR compiler passes.

TorchScript (torch.jit.script)

TorchScript is a strict Python subset which is modeled faithfully in the JIT IR. Additionally, TorchScript can represent a full torch.nn.Module object graph (hierarchy). This results in a significant amount of work needing to be done by the frontend to lower it to the backend contract:

- The torch.nn.Module hierarchy must be lowered to the backend contract, which does not allow any program state.
- The program must be converted to value semantics (functionalized).
- Shapes and dtypes must be inferred.
- Many "Python-isms" must be simplified away, such as list appends, string operations, etc.

Because TorchScript does not naturally give shapes or dtypes, we usually require the user to annotate a set of expected shapes and dtypes of any arguments. We then propagate those throughout the program.

torch.jit.trace produces JIT IR with shapes and dtypes already, but no value semantics. And often users want to erase the shapes in the trace to allow dynamic shapes for the trace. Additionally, the Python-level data structures and APIs are very parallel between torch.jit.script and torch.jit.trace, so we consider both of those as the same from the perspective of the responsibilities of the compiler. Both are accessed via the torch_mlir.torchscript.compile Python API.

Modeling the torch.nn.Module object (IValue) hierarchy for TorchScript

PyTorch consistently models a subset of Python objects with its concept of IValue (interpreter value). These are used throughout PyTorch to represent Python values. When one torch.jit.script's a torch.nn.Module, the result is actually an IValue that represents the module, with a hierarchy of children IValue's. Strictly speaking, JIT IR torch::jit::Graph's are only used to represent the bodies of methods on the modules. So in addition to importing the JIT IR, we also need to import the IValue's. This happens inside ivalue_importer.cpp.

Most of the IValue modeling can reuse torch dialect ops that already exist otherwise, such as torch.constant.int to represent an int in the object graph. However, special IR constructs are needed for modeling the torch.nn.Module's themselves.

An example is:

```
torch.class_type @c {
  torch.attr "b" : !torch.bool
  torch.attr "i" : !torch.int
  torch.attr "f" : !torch.float
  torch.attr "t" : !torch.tensor
  torch.method "get_tensor", @get_tensor
}
func.func private @get_tensor(%arg0: !torch.nn.Module<"c">) -> !torch.tensor {
  %2 = torch.prim.GetAttr %arg0["t"] : !torch.nn.Module<"c"> -> !torch.tensor
  return %2 : !torch.tensor
}

%true = torch.constant.bool true
%int3 = torch.constant.int 3
%float4.250000e01 = torch.constant.float 4.250000e+01
%0 = torch.tensor.literal(dense<1.000000e+00> : tensor<1xf32>) : !torch.tensor
%1 = torch.nn_module {
  torch.slot "b", %true : !torch.bool
  torch.slot "i", %int3 : !torch.int
  torch.slot "f", %float4.250000e01 : !torch.float
  torch.slot "t", %0 : !torch.tensor
} : !torch.nn.Module<"c">
```

See the documentation for the ops for more information on the semantics of this form.

Lowering TorchScript to the backend contract

The torchscript-module-to-torch-backend-pipeline contains the set of simplifications used convert TorchScript to the backend contract. At a high level, it consists of the following transformations:

1. GlobalizeObjectGraph: This takes the IValue object graph and converts it into a flat list of globals (see torch.global_slot and related ops).
2. LowerToBackendContract: This pass iteratively applies a simplification pipeline until the backend contract is reached. The simplification pipeline consists of:
   - Standard canonicalization.
   - Shape and Dtype refinement. See abstract_interp_lib.md for detail
   - Decomposing ops into more primitive ops. See DecomposeComplexOps.

Layering of the PyTorch Dependency

One of the core principles of our Torch-MLIR <-> PyTorch interop is that anything that links against PyTorch must interact with MLIR through the Torch-MLIR C API. This bypasses a number of very complex dependency and shared library issues.

Additionally, we maintain the invariant that the core MLIR compiler code (in lib/ and include/) never has a build dependency on PyTorch itself. This strict isolation avoids a number of complex dependency issues and ensures that torch-mlir-opt and similar debugging tools always provide the excellent development and debugging experience that MLIR developers expect. Sometimes, certain highly stable enums and related logic must be shared with upstream PyTorch, and for those we copy code from PyTorch into TorchUpstream.h.

The Backends

Torch-MLIR provides 3 built-in backends, which take the backend contract IR and lower it to the requirements of each backend. The 3 backends are:

- linalg on tensors (+ arith, tensor, etc.)
- TOSA
- StableHLO

The Linalg Backend (Linalg-on-Tensors)

Code: https://github.com/llvm/torch-mlir/tree/main/lib/Conversion/TorchToLinalg

The Linalg-on-Tensors backend was the first backend that we added, and it is still the most complete. It fully supports dynamic shapes (known number of dimensions but arbitrary dynamic dimension sizes). Since linalg was originally designed as a dialect for transformations, it can be too low-level for certain consumers.

The TOSA Backend

Code: https://github.com/llvm/torch-mlir/tree/main/lib/Conversion/TorchToTosa

The TOSA backend was the second backend that we added. It remains preferred by many users (especially "hardware" or "hardware-adjacent" folks). Some of its characteristics are:

- It is tied to a spec with a really clear "ISA-like" expository style that resonates with a lot of folks
- The coarse-grained named-op approach is a good match for the many compilers that are designed that way.
- It has really good support for quantization / integer data types.
- It has clear versioning/stability guarantees on the op semantics.
- It is extremely solid with static shapes (and many of its users only care about static shapes, so that's fine).

The StableHLO Backend

Code: https://github.com/llvm/torch-mlir/tree/main/lib/Conversion/TorchToStablehlo

The StableHLO backend was the third backend that we added, and it offers a reasonable blend of the benefits of the other two.

- It is a coarse-grained named-op approach.
- It has a pretty clear spec for most of the ops (with a bit of mental translation and hoping that StableHLO is the same as HLO): https://www.tensorflow.org/xla/operation_semantics

- It functionally supports dynamic shapes (though not as coherent and consistent as Linalg-on-Tensors, and the dynamic shape support falls outside the wonderful HLO docs above).
- It appears to be pretty tied to HLO (which is highly mature) so most of the op surface area doesn't change too much.
- It has a different set of principles than TOSA which tend to make it more expressive at the cost of having a larger abstraction gap from hardware. For example, TOSA limits (for highly considered reasons) the number of dimensions that certain operators can handle to 1D-4D, when from a purely algebraic perspective there isn't a good reason to not be more general. Similarly, more general forms of reduction and scatter also fall into StableHLO nicely while TOSA's principles tend to bias it away from that.

Backend Implementation

All the backends are implemented using the MLIR Dialect Conversion infrastructure. This involves converting the torch dialect types to other types, so we closely follow the principles from the "Type Conversions the Not-So-Hard Way" talk (slides, recording). We follow the standard {include,lib}/Conversion/TorchTo* convention used in MLIR for conversion passes.

For type conversion, we provide BackendTypeConversion.cpp and BackendTypeConversionPasses.cpp which provide a default conversion from torch dialect types to the builtin tensor type and scalar integer/float types. These are not the right choice for all backends, but can be copied and adapted by backends. These files closely follow the "Type Conversions the Not-So-Hard Way" talk.

Testing

See development.md for more details on running tests.

Torch-MLIR has two types of tests:

1. End-to-end execution tests. These compile and run a program and check the result against the expected output from execution on native Torch. These use a homegrown testing framework (see framework.py) and the test suite lives at python/torch_mlir_e2e_test/test_suite.
2. Compiler and Python API unit tests. These use LLVM's lit testing framework. For example, these might involve using torch-mlir-opt to run a pass and check the output with FileCheck. lit is flexible enough to unit test various Python pieces, importers, and LTC this way as well.

Why so much end-to-end testing?

Torch-MLIR places a heavy emphasis on end-to-end testing for the following reasons:

Reason 1: Even if a compiler pass produces the output IR that the author expected, that output IR may not correctly implement the semantics of the op. This is especially true for complex, often-poorly-specified deep learning operators that Torch-MLIR is mainly concerned with. It is critical to run these against the source of truth to ensure correct implementation.

Reason 2: There are many patterns in Torch-MLIR's backends that really just expand one op into other ops without any real logic. When we started Torch-MLIR, we were very religious about always having .mlir unit tests even for these "macro expansion" patterns, but we found that these tests 1) Never caught a bug 2) Interfered with refactoring / caused spurious extra work (changing op syntax, etc.). There is not much point to having a bunch of tests like this, which are basically just rewriting the builder calls in a different syntax:

```
// MyPass.cpp

b.create<FooOp>(...)

b.create<BarOp>(...)

// test.mlir

// CHECK: foo

// CHECK: bar
```

Such a test is simply checking that the implementation of an op is the way it is. There is no way to change the implementation while having the test pass. So the test is fully redundant with the implementation.

Because of this, many Torch-MLIR patches adding support for new ops have no .mlir unit tests, and only include end-to-end test(s). We generally make sure that our end-to-end tests are as targeted as possible. As a result, when debugging end-to-end test failures, the resulting reproducers (which our test framework automatically produces for failures) are usually already fully reduced test cases.

Do's and Don'ts for unit vs end-to-end testing.

DO use an end-to-end test if you are implementing a new op or extending the support for an existing op.

DO use a unit test if your lowering for an op has multiple cases / logic. This also helps future maintainers of the lowering to see in one place all the different edge cases of the op that you had to handle. (these can be easily reduced out of all the end-to-end tests you added).

DON'T use a unit test if your lowering pattern could be described as a trivial "macro expansion" of one op into another op or set of ops. That is, if you feel like your unit test is just rewriting b.create<...>(...) into CHECK: ... then it is probably not a useful unit test.

With the exceptions above, all changes should include appropriate unit tests, as is standard in the LLVM and MLIR community. This includes full coverage of all canonicalizations, pretty printing, passes, errors, and diagnostics.

The RefBackend (Reference Backend)

In order to run end-to-end tests, Torch-MLIR needs an end-to-end flow. Thankfully, upstream MLIR has just enough pieces to precariously put one together that is enough for testing.

The RefBackend consists of a few minor C++ passes filling in some corners missing upstream and Python glue logic to pull together upstream functionality into a working system.

The RefBackend accepts Linalg-on-Tensors as input. It mainly just bufferizes the ops and lowers them to loops. Note that TOSA and StableHLO (via MHLO) support lowering to Linalg-on-Tensors, so all our end-to-end testing bottoms out on RefBackend.

The RefBackend is absolutely not suitable for any production use case. It leaks memory, doesn't support any error handling, performs no optimizations, and probably a bunch of other horrible things. We are patiently awaiting for the upstream MLIR community to produce a viable end-to-end flow with better characteristics.

Presentations and Talks

- 2021-10-07: MLIR ODM: Introduction to Torch-MLIR. (recording and slides)
- 2022-08-20: Overview of Torch-MLIR passes. (recording and slides)