Buddy Compiler: An MLIR-Based Compilation Framework for Deep Learning Co-Design

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Buddy Compiler is a domain-specific compiler framework.

We are building a co-design ecosystem based on MLIR and RISC-V.

We hope to achieve deep co-design from DSL to DSA.

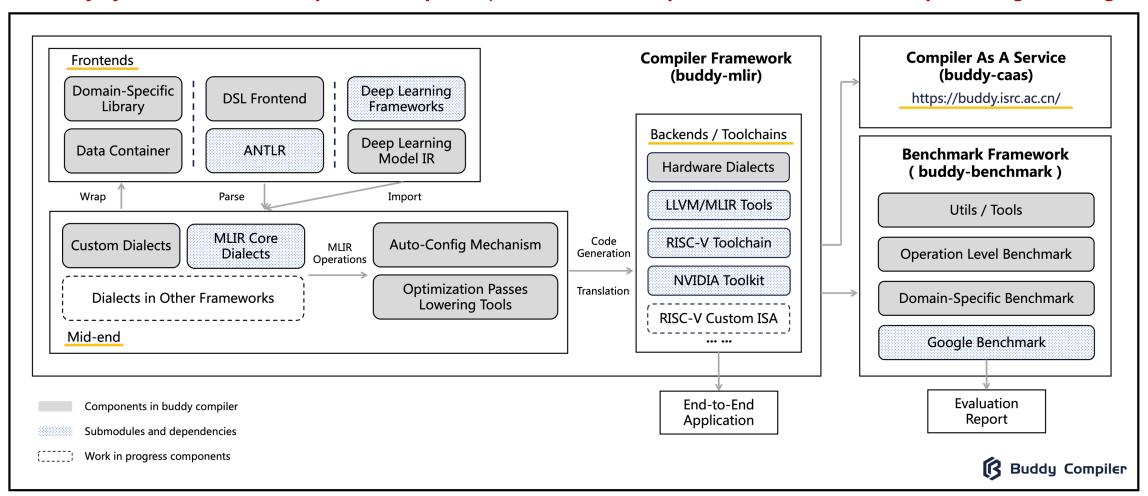
Deep co-design for deep learning!



Buddy Compiler Overview



"Buddy System" for Domain-Specific Compilers | MLIR-Based Compilation Framework for Deep Learning Co-Design



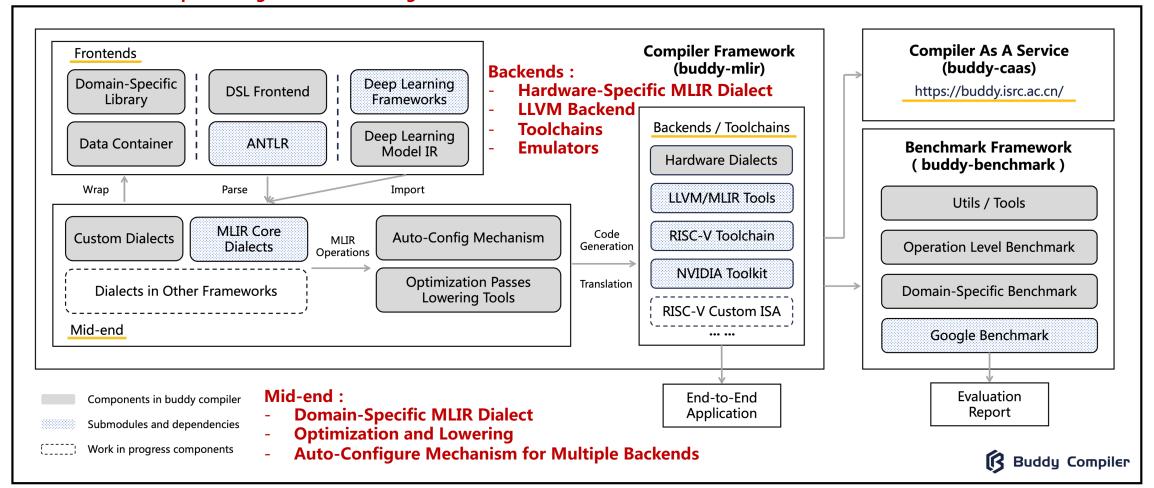
Homepage: https://buddy-compiler.github.io/ GitHub: https://github.com/buddy-compiler

Buddy Compiler Overview



Frontends: Domain-Specific Libraries, DSL Framework,
Deep Learning Frameworks Integration

Online Service: Ecosystem Entry
(Demonstrate, Share, and Debug)



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Benchmark Framework:

- Benchmark Cases for Multiple Levels
- Evaluation and Visualization Tools



MLIR and RISC-V are a perfect match for co-design!

Because they are both modular and extensible.

The unified ecosystem can unlock more co-design opportunities.



Buddy Compiler Deep Learning Co-Design







Multimodal Representations

Buddy Compiler Domain-Specific Dialects







Deep Learning Model Representations

MLIR TOSA / Linalg Dialect

Vector Representation

- Vector Dialect
- RVV Dialect
- LLVM VP Intrinsic

MLIR Core Dialects

- MemRef Dialect
- Affine Dialect
- SCF Dialect

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Gemmini Dialects

- Gemmini Operation
- Gemmini Intrinsic Operation
- Custom LLVM Extension

LLVM | RISC-V GNU Toolchain | Emulators

SIMD Processor (RISC-V P Extension) **Vector Processor** (RISC-V V Extension)

GPGPU (e.g. Ventus)

DSA (e.g. Gemmini)

Preprocessing + Deep Learning Workload

- Preprocessing Operation Optimization
- Unified Data Structure to Avoid Copy Overhead
- Potential Operation Fusion Opportunity

Compiler Passes + Hardware Architecture

- Design Representations for Hardware Features
- Configure Passes by Hardware Information
- Potential Auto-Tuning / DSE Opportunity



The key to co-design is unified abstraction and presentation.

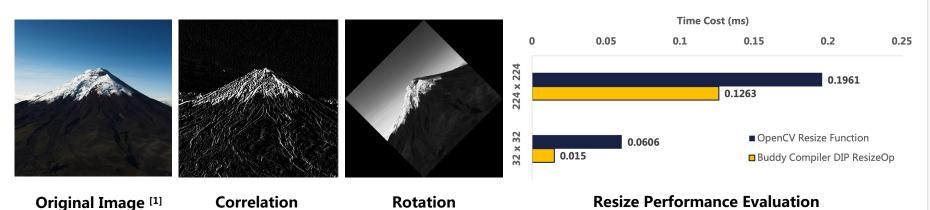
MLIR can unify domain-specific applications and languages together.



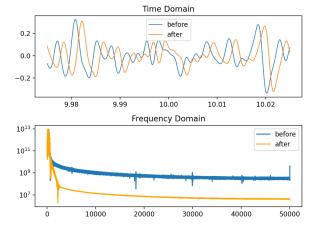
Domain-Specific Application Support

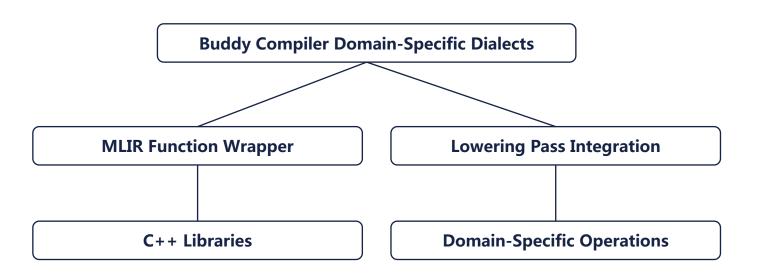


Image Processing



Audio Processing^[2]





C++ Libraries

Domain-Specific Operations

- [1] The origin image is from MediaStorm https://www.ysjf.com/materialLibrary
- [2] The origin audio is from NASA 's recording of sound on Mars https://www.nasa.gov/connect/sounds/index.html

Domain-Specific Language Support



```
def main() {
                                                                   dsl-compiler tensor-add.toy -emit=jit
  var a<2, 2> = [1, 2, 3, 4, 5, 6];
                                                                                                                                       2.000000 4.000000
  var b<2, 2> = [[1, 2], [3, 4]];
                                                                                                                                       6.000000 8.000000
   print(a + b);
DSL Source Code
                                                def AddOp : Toy Op<"add",</pre>
                                                    [Pure, DeclareOpInterfaceMethods<ShapeInferenceOpInterface>]> {
 expression:
                                                  . . . . . . .
   . . . . . .
     expression Add expression
                                                  let arguments = (ins F64Tensor:$lhs, F64Tensor:$rhs);
                                                  let results = (outs F64Tensor):
ANTLR Syntax Definition (g4)
                                                MLIR Operation Definition
      virtual std::any visitExpression(ToyParser::ExpressionContext *ctx) override {
                                                                                        module {
       mlir::Value value;
                                                                                         toy.func @main() {
                                                                                            %0 = toy.constant dense<[1.0, 2.0, 3.0, 4.0]> : tensor<4xf64>
       else if (ctx->Add() || ctx->Mul()) {
                                                                                            %1 = toy.reshape(%0 : tensor<4xf64>) to tensor<2x2xf64>
         mlir::Value lhs = std::any_cast<mlir::Value>(visit(ctx->expression(0)));
                                                                                            %2 = toy.constant dense<[[1.0, 2.0], [3.0, 4.0]]> : tensor<2x2xf64>
         mlir::Value rhs = std::any cast<mlir::Value>(visit(ctx->expression(1)));
                                                                                            %3 = toy.reshape(%2 : tensor<2x2xf64>) to tensor<2x2xf64>
         mlir::Location loaction =
                                                                                            %4 = toy.add %1, %3 : (tensor<2x2xf64>, tensor<2x2xf64>) -> tensor<*xf64>
             loc(ctx->start->getLine(), ctx->start->getCharPositionInLine());
                                                                                            toy.print %4 : tensor<_*xf64>
         if (ctx->Add())
                                                                                            toy.return
           value = builder.create<mlir::toy::AddOp>(loaction, lhs, rhs);
```

Generated MLIR

ANTLR Visitor



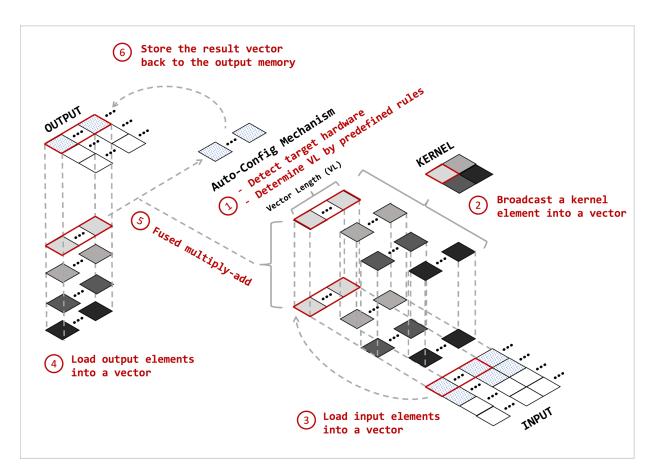
IRs are unified, and optimization should not be fragmented.

No one wants to port an algorithm to every platform!



Optimization for Multiple Backends

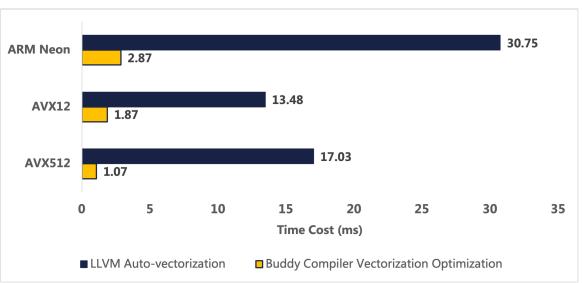




Broadcast-Based Vectorization Algorithm for Convolution Operation

1. Combination of Multiple Optimization Strategy

- High-Level Optimization Algorithm
- Compilation Optimization
- 2. Using MLIR Vector Dialect to Achieve Portable Optimization
- 3. Detect Target Hardware and Configure Optimization Pass



MLIR Convolution Operation (Conv2D) Comparison (Input Size: 1024 x1024 Kernel Size: 3 x 3)





Of course, co-design should consider hardware features!

If you do need to expose those hardware features to the compiler, let's add a new IR abstraction.



RISC-V High-Performance Hardware Support - RVV



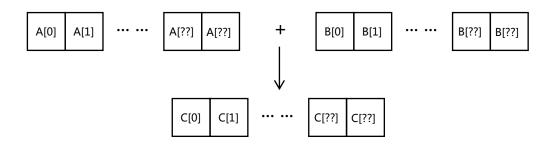
No SETVL Operation

Cannot Set Dynamic VL

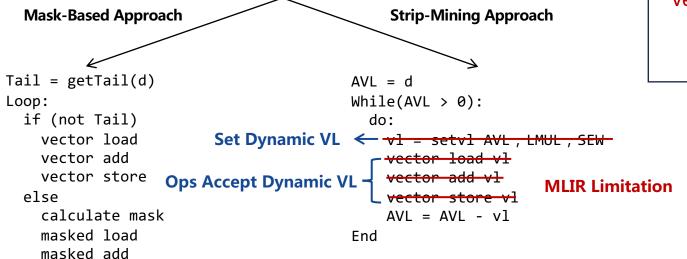
RVV Tail Processing

masked store

end if End loop



Get the application vector length (d) at runtime



Information Required at Compile Time:

- Dynamic VL Configuration
 - AVL Configuration
 - LMUL Configuration
 - SEW Configuration
 - Operations Dynamic VL Operand

Vector operations do not accept dynamic VL parameters.

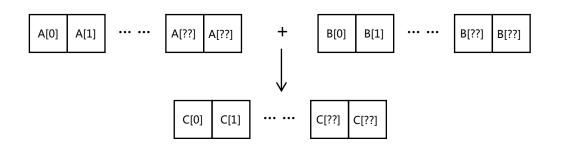
%0 = arith.addf %v, %v : vector<8xf32>

RISC-V High-Performance Hardware Support - RVV

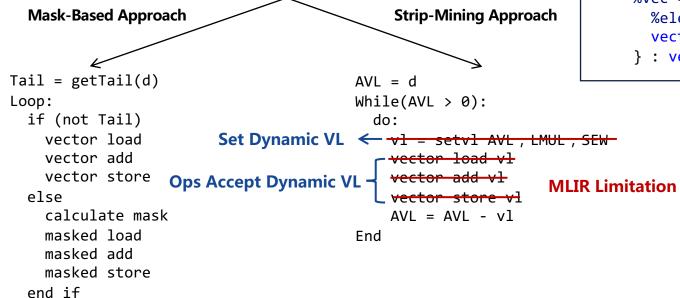


RVV Tail Processing

End loop



Get the application vector length (d) at runtime



```
Add RVV MLIR Support (balance the generality and specificity)
```

1 – RVV-Specific Dialect SetVL Operation: Set dynamic vector length

```
%vl = rvv.setvl %avl, %sew, %lmul : index
AVL = Application Vector Length
SEW = Selected Element Width
LMUL = Vector Register Group Multiplier
```

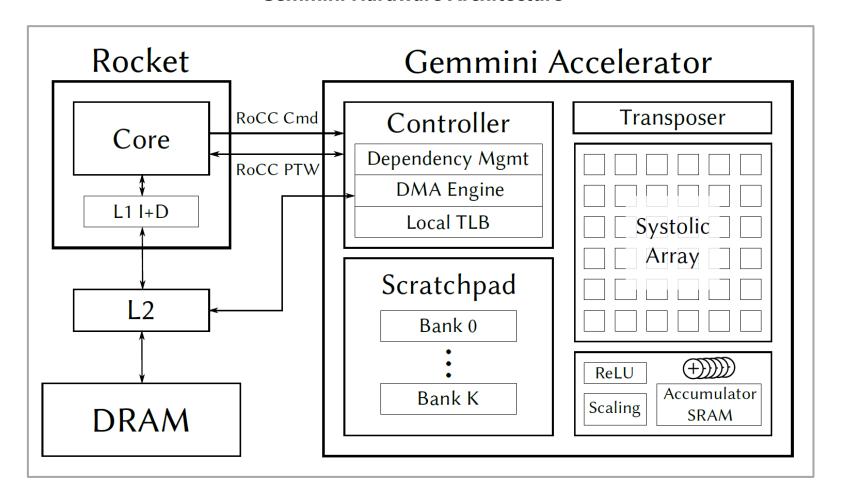
2 – Generic Vector Predication Operation

```
%vec = vector_exp.predication %mask, %vl : vector<[4]xi1>, i32 {
    %ele = vector.load %m[%c0, %c0]: memref<8x8xi32>, vector<[4]xi32>
    vector.yield %ele : vector<[4]xi32>
} : vector<[4]xi32>
```

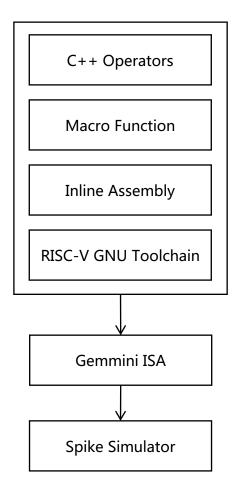
RISC-V High-Performance Hardware Support - Gemmini



Gemmini Hardware Architecture^[1]

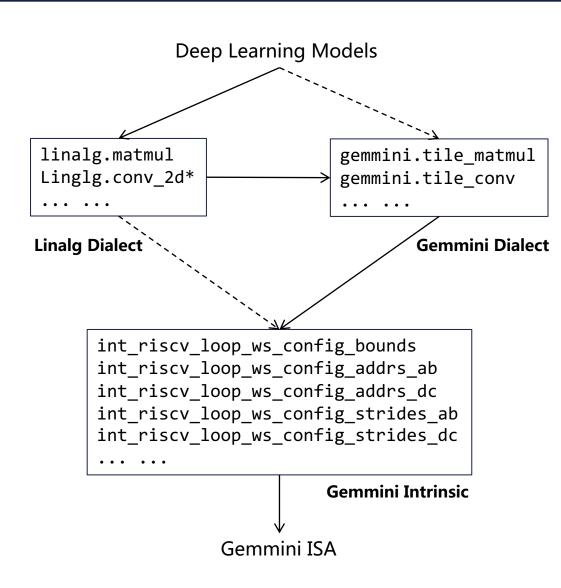


Gemmini Software Stack



RISC-V High-Performance Hardware Support - Gemmini





Buddy Compiler Gemmini Support Gemmini Software Stack C++ Operators **MLIR Operations** Gemmini MLIR Dialect Macro Function Gemmini LLVM **Inline Assembly** Intrinsic RISC-V GNU Toolchain RISC-V GNU Toolchain Gemmini ISA

Spike Simulator

What's Next ...







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Thanks

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