TC-CIM: Empowering Tensor Comprehensions for Computing In Memory

Andi Drebes¹ Lorenzo Chelini^{2,3} Oleksandr Zinenko⁴
 Albert Cohen⁴ Henk Corporaal² Tobias Grosser⁵
 Kanishkan Vadivel² Nicolas Vasilache⁴

¹Inria and École Normale Supérieure ²TU Eindhoven ³IBM Research Zurich ⁴Google ⁵ETH Zurich

01/22/2020

Detecting Operations for Accelerators



Goal: Reliably detect operations for efficient offloading

Detecting Operations for Accelerators



- Goal: Reliably detect operations for efficient offloading
- At which stage?
- On which representation?
- Create reusable infrastructure











Compute In Memory (CIM)



- Interweave Computation and Storage
- Example: Memristor-based Architecture from MNEMOSENE project (https://www.mnemosene.eu)

Compute In Memory (CIM)



- Interweave Computation and Storage
- Example: Memristor-based Architecture from MNEMOSENE project (https://www.mnemosene.eu)
- High energy efficiency and throughput with fixed functions (e.g., matrix multiplication)

Detecting Accelerated Operations for CIM



- Goal: Reliably detect operations for efficient offloading
- At which stage?
- On which representation?
- Create reusable infrastructure

Detecting Accelerated Operations for CIM



- Goal: Reliably detect operations for efficient offloading
- At which stage?
- On which representation?
- Create reusable infrastructure

Tensor Comprehensions

Math-like notation

- Expresses operations on tensors
- Only information needed to define operation unambiguously
- Compiler infers shapes and iteration domains

Tensor Comprehensions

Math-like notation

- Expresses operations on tensors
- Only information needed to define operation unambiguously
- Compiler infers shapes and iteration domains

Example:

```
def mv(float(M,K) A, float(K) x) -> (C)
{
    C(i) +=! A(i,k) * x(k)
}
```

Tensor Comprehensions: Compilation



Integration of Loop Tactics



```
 \begin{array}{l} \text{def kernel(} \\ & \text{float(M,N) A,} \\ & \text{float(M,K) B} \rightarrow (\text{C}) \\ \{ & \dots \\ & \text{C(i,k) } \leftarrow ! \\ & \text{A(i, n) } \ast B(n, k) \\ & \dots \\ \} \end{array}
```















Loop Tactics: Tree Matchers

Tree Matcher defines pattern for subtree and captures nodes

```
schedule_node body;
schedule_node initBody;
schedule_node schedule;
auto matcher =
    band(schedule,
        sequence(
        filter(initBody,
        hasGemmInitPattern,
        leaf()),
```



Loop Tactics Access Relation Matchers

Access Relation Matcher: Matches tensor accesses

```
auto hasGemmPattern = [&](schedule node node) {
  auto _i = placeholder();
  auto _j = placeholder();
  auto _k = placeholder();
  auto _A = arrayPlaceholder();
  auto _B = arrayPlaceholder();
  auto _C = arrayPlaceholder();
  auto reads = /* get read accesses */;
  auto writes = /* get write accesses */;
  auto mRead = allOf(
      access(_C, _i, _j),
      access(_A, _i, _k),
      access(_B, _k, _j));
  auto mWrite = allOf(access(_C, _i, _j));
  return match(reads, mRead).size() == 1 &&
         match(writes, mWrite).size() == 1;
};
```

Loop Tactics Access Relation Matchers

Access Relation Matcher: Matches tensor accesses

```
auto hasGemmPattern = [&](schedule node node) {
  auto _i = placeholder();
  auto _j = placeholder();
  auto _k = placeholder();
  auto _A = arrayPlaceholder();
  auto _B = arrayPlaceholder();
  auto _C = arrayPlaceholder();
  auto reads = /* get read accesses */;
  auto writes = /* get write accesses */;
  auto mRead = allOf(
      access(_C, _i, _j),
      access(_A, _i, _k),
      access(_B, _k, _j));
  auto mWrite = allOf(access(_C, _i, _j));
 return match(reads, mRead).size() == 1 &&
         match(writes. mWrite).size() == 1;
};
```

Additionally match leaf expressions

Drebes et al. - TC-CIM: Empowering Tensor Comprehensions for Computing In Memory

```
auto builder =
mark ([&]() { return marker() },
band([&]() { return schedule.getSchedule() },
sequence(
filter([&]() { return initBody.getFilter() }),
filter([&]() { return body.getFilter() })));
```

Loop Tactics: Tree Builders



```
auto builder =
mark ([&]() { return marker() },
band([&]() { return schedule.getSchedule() },
sequence(
filter([&]() { return initBody.getFilter() }),
filter([&]() { return body.getFilter() })));
```

Loop Tactics: Tree Builders



```
auto builder =
mark ([&]() { return marker() },
band([&]() { return schedule.getSchedule() },
sequence(
filter([&]() { return initBody.getFilter() }),
filter([&]() { return body.getFilter() })));
```

Loop Tactics: Tree Builders



```
auto builder =
mark ([&]() { return marker() },
band([&]() { return schedule.getSchedule() },
sequence(
filter([&]() { return initBody.getFilter() }),
filter([&]() { return body.getFilter() })));
```

Implemented Matchers

- Matrix-matrix multiplications
- Matrix-vector multiplications

Implemented Matchers

- Matrix-matrix multiplications
- Matrix-vector multiplications

Benchmarks

Benchmarks: mm, mv, batchMM, 3mm, 4cmm, mlp3

Implemented Matchers

- Matrix-matrix multiplications
- Matrix-vector multiplications

Benchmarks

Benchmarks: mm, mv, batchMM, 3mm, 4cmm, mlp3

Static Impact

- Percentage of detected patterns in the code
- Test robustness against prior Transposition / Tiling

Implemented Matchers

- Matrix-matrix multiplications
- Matrix-vector multiplications

Benchmarks

Benchmarks: mm, mv, batchMM, 3mm, 4cmm, mlp3

Static Impact

- Percentage of detected patterns in the code
- ► Test robustness against prior Transposition / Tiling

Dynamic Impact

Dynamic instruction count unoptimized vs. optimized version

Detected Patterns in the Code



Breakdown of Dynamic Host CPU Instructions



Positioning in the Pipeline



Matching after Affine Scheduling without Rescheduling:

- Leverages enabling transformations (e.g., fusion, tiling)
- Initial schedule as canonical form (e.g., permutability, band coalescing)
- No feedback for transformations (e.g., no architecture-specific tiling, fusion decisions, etc.)
- Complexity of matchers rises with prior transformations

Positioning in the Pipeline



Matching after Affine Scheduling without Rescheduling:

- Leverages enabling transformations (e.g., fusion, tiling)
- Initial schedule as canonical form (e.g., permutability, band coalescing)
- No feedback for transformations (e.g., no architecture-specific tiling, fusion decisions, etc.)
- Complexity of matchers rises with prior transformations
- Matching earlier (at higher level of abstraction)
 - More high-level information for matchers
 - Simpler matchers & builders
 - Less / no benefits from affine transformations

Summary and Future Work

Summary

- TC-CIM: Compilation flow for (CIM) accelerators
- Integration of Loop Tactics into Tensor Comprehensions
- Reliable detection + significant dynamic impact

Summary and Future Work

Summary

- TC-CIM: Compilation flow for (CIM) accelerators
- Integration of Loop Tactics into Tensor Comprehensions
- Reliable detection + significant dynamic impact

Future Work

- Explore positioning in the pipeline
- More complex matchers: fusion / minimizing data transfers
- Matching in MLIR (e.g., raise from lower-level dialects to high-level dialects)