

HYPERF: End-to-End Autotuning Framework for High-Performance Computing

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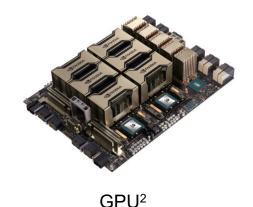
Republic of Korea

*Equal contribution

Modern High-Performance Computing Systems

- Modern HPC platforms utilize heterogeneous and parallel hardware for high throughput
 - Growing demands from diverse application domains
 - Scientific simulations, big data processing, ML/DL workloads
 - Increasing computational requirements driven by large-scale data









FPGA³ NPU⁴





^[1] https://no.mouser.com/new/intel/intel-5th-gen-xeon-processors

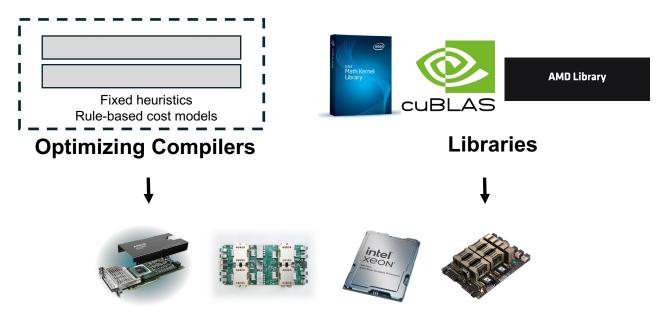
^[2] https://developer.nvidia.com/blog/introducing-hgx-a100-most-powerful-accelerated-server-platform-for-ai-hpc/

^[3] https://www.amd.com/ko/products/accelerators/alveo/v80.html

^[4] https://korea.googleblog.com/2017/05/google-cloud-offer-tpus-machine-learning.html

Software Stacks for HPC

- Optimizing the software stack is crucial for harnessing HW parallelism
 - Parallel programming models, compiler/runtime, libraries





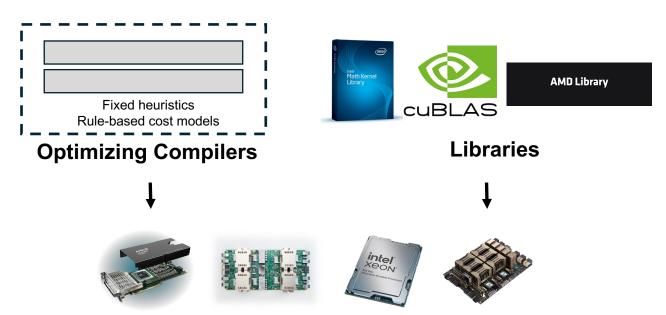






Software Stacks for HPC

- Optimizing the software stack is crucial for harnessing HW parallelism
 - Parallel programming models, compiler/runtime, libraries
- Complex and diverse hardware poses optimization challenges
 - Repeated engineering effort is required for hand-tuned libraries
 - Fixed heuristic-based optimizations often lead to suboptimal performance



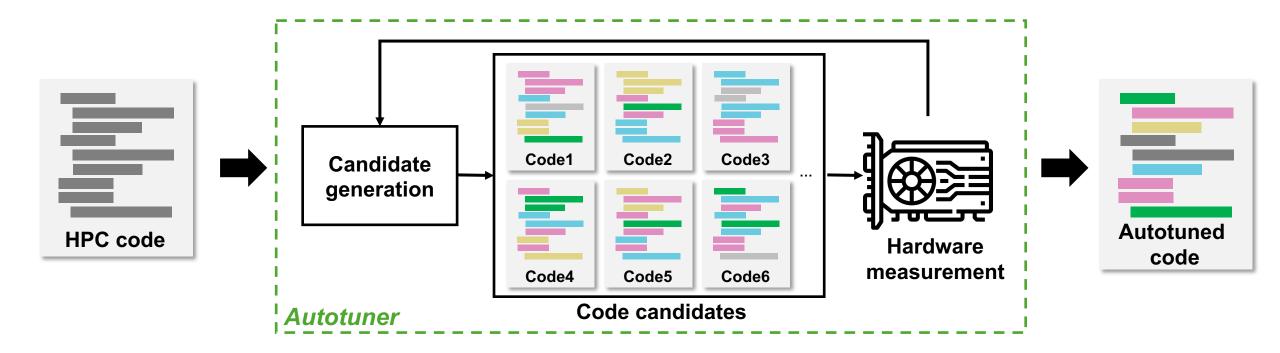






Autotuning Approaches

- Search-based, iterative optimization
 - Generate candidates for a given code
 - Search for high-performing versions through hardware evaluations



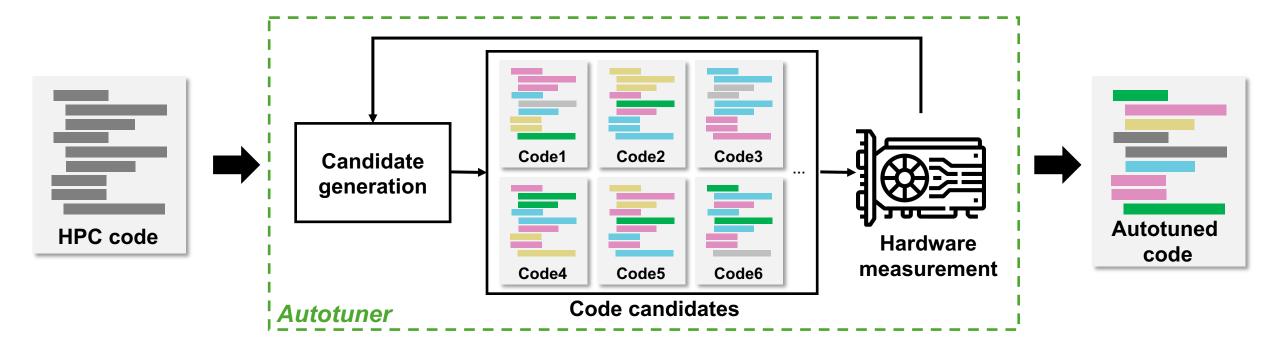






Autotuning Approaches

- Search-based, iterative optimization
 - Generate candidates for a given code
 - Search for high-performing versions through hardware evaluations
- → Adaptive and flexible, not requiring re-implementation

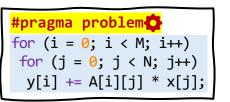








• Pragma-based approaches[1-3] annotate low-level code to guide optimization decisions



GEMV low-level code





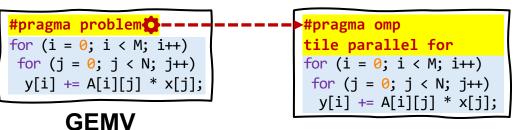




^[2] Ansel, Jason, et al. "Opentuner: An extensible framework for program autotuning."

- Pragma-based approaches[1-3] annotate low-level code to guide optimization decisions
- Autotuner uses user annotations to apply different compiler and optimization parameters and generate candidates

Configuring directives without modifying low-level code



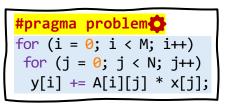
low-level code



^[2] Ansel, Jason, et al. "Opentuner: An extensible framework for program autotuning." [3] Wu, Xingfu, et al. "ytopt: Autotuning scientific applications for energy efficiency at large scales."

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Configuring directives without modifying low-level code





GEMV low-level code

```
#pragma omp
tile parallel for
for (i = 0; i < M; i++)
  for (j = 0; j < N; j++)
   y[i] += A[i][j] * x[j];

#pragma omp simd
...

#pragma omp simd tile
...

#pragma omp simd unroll
...</pre>
```

Candidate generation



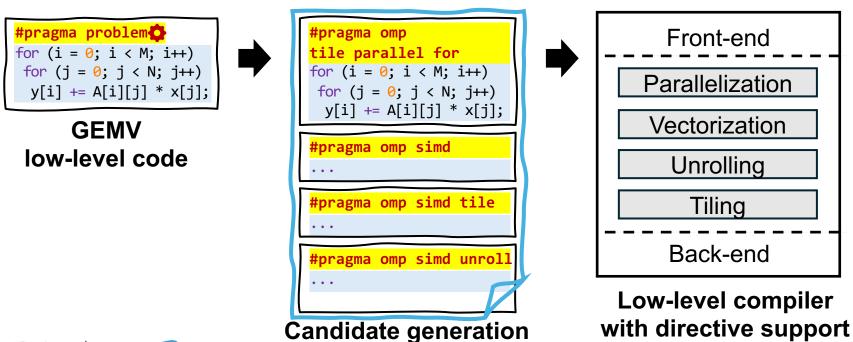






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 - How codes are transformed is determined by low-level compiler implementations

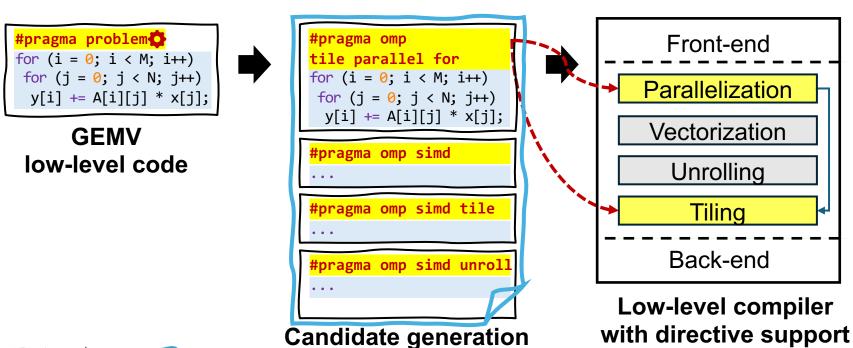








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Pragmas only guide optimization passes



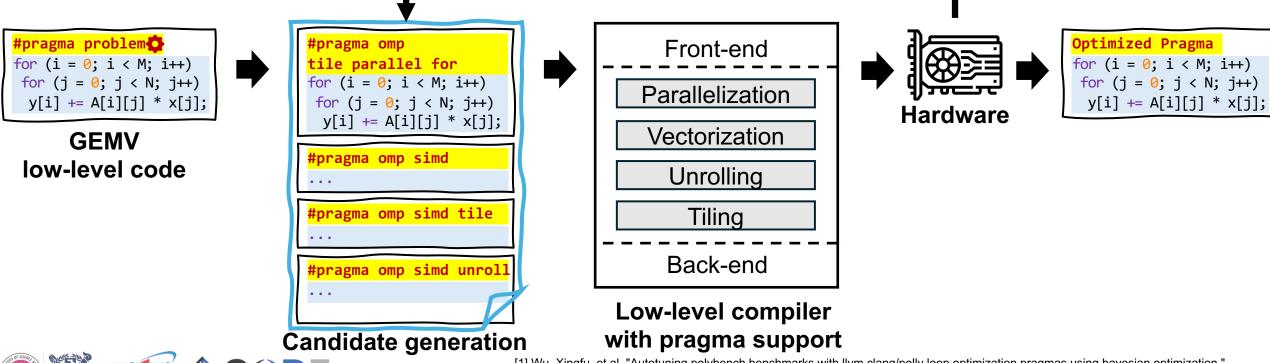






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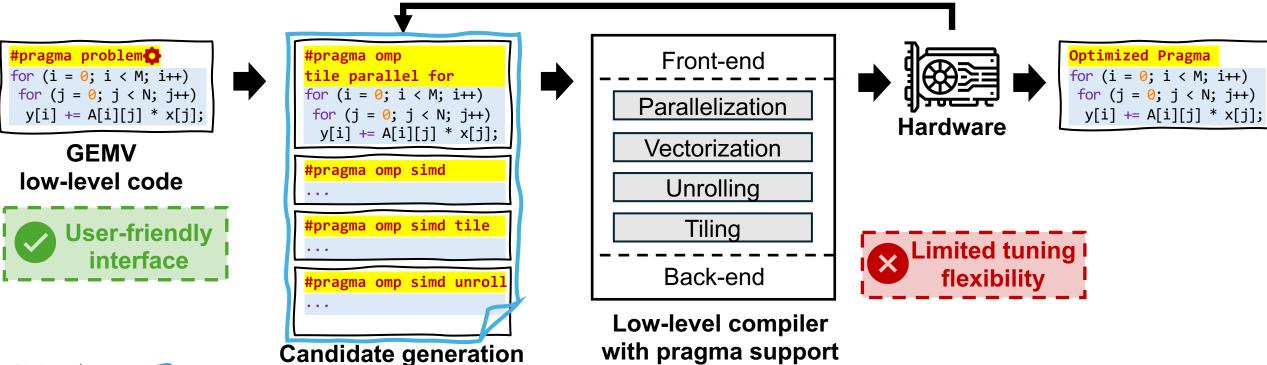








- Enables autotuning of existing low-level code
- Autotuning scope and flexibility are inherently limited by the original code structure and compiler capabilities





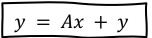




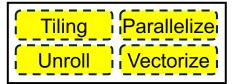


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• Schedule-based approaches[1-2] use domain-specific IRs to specify high-level algorithms and their implementations



GEMV Algorithm IR



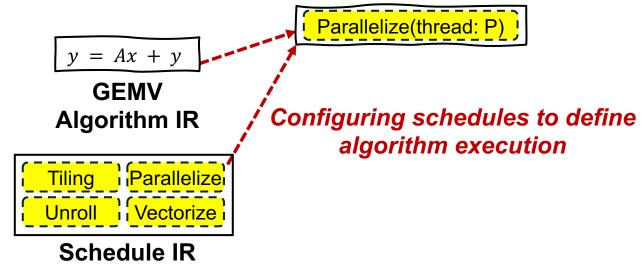
Schedule IR







- Schedule-based approaches[1-2] use domain-specific IRs to specify high-level algorithms and their implementations
 - Autotuner generates candidates by composing "schedules" and assigning randomized parameter values





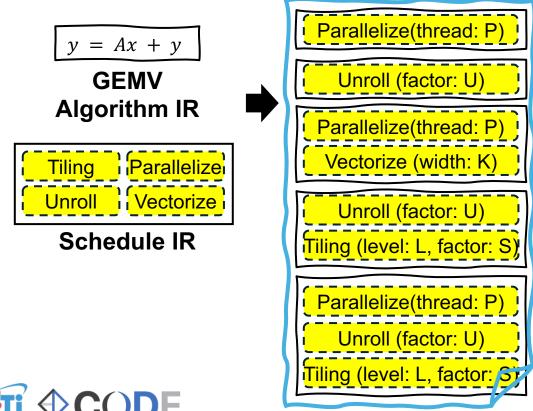




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Candidate generation

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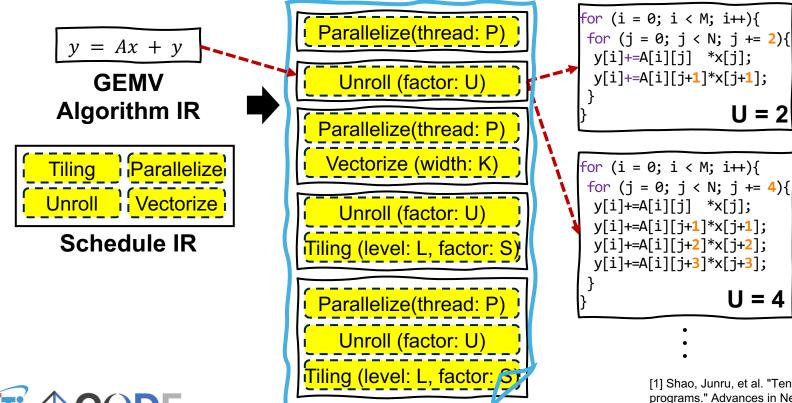








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Candidate generation

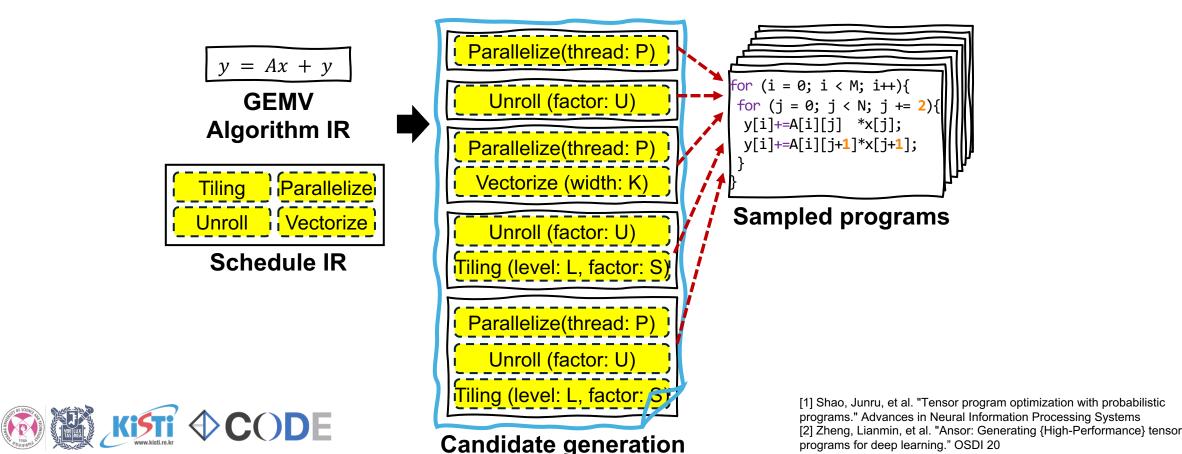




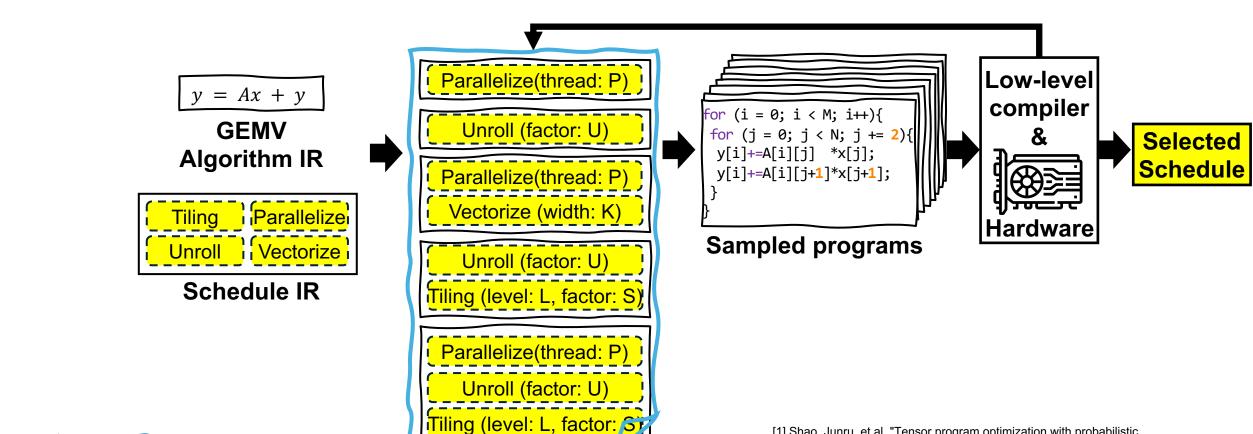




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Candidate generation

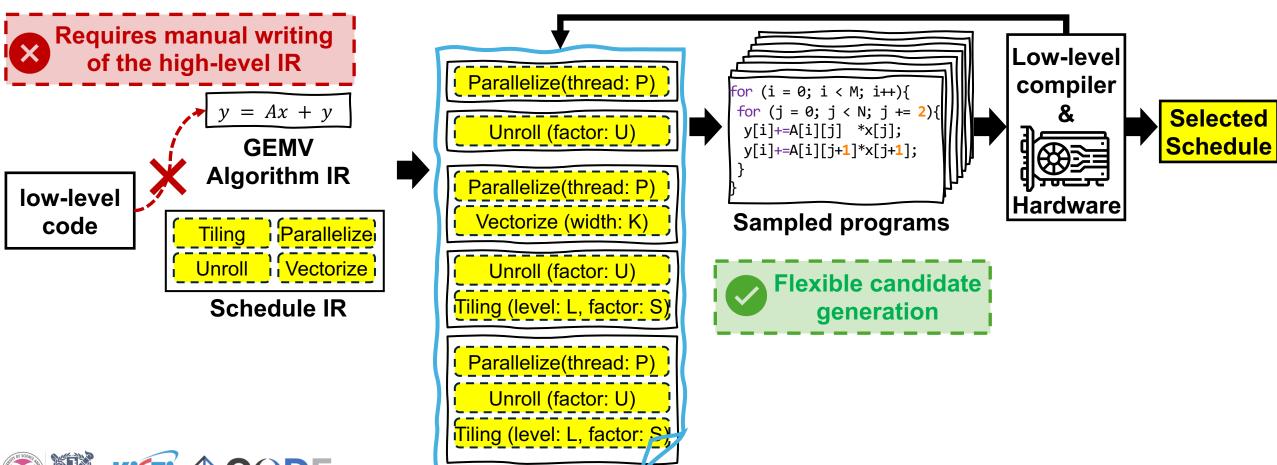




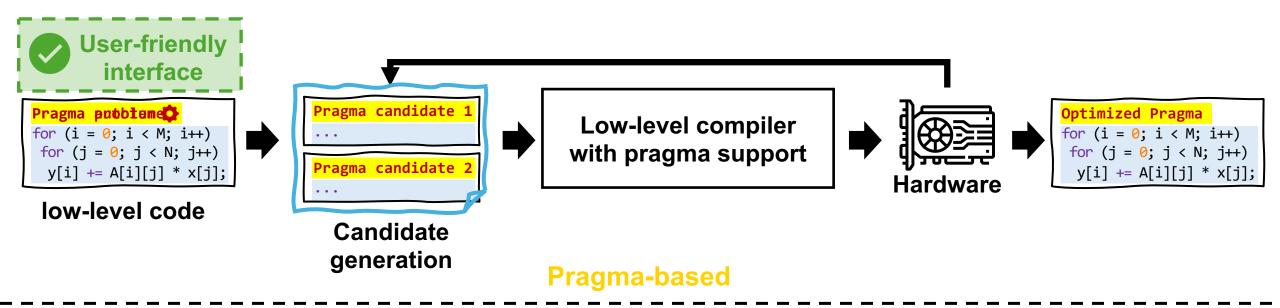


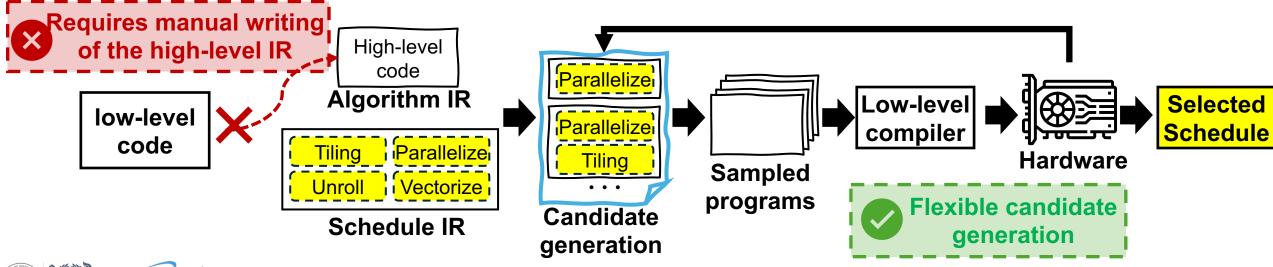


- Enables flexible candidate generation with a rich search space
- Requires definitions of high-level algorithm and schedule IRs



Candidate generation





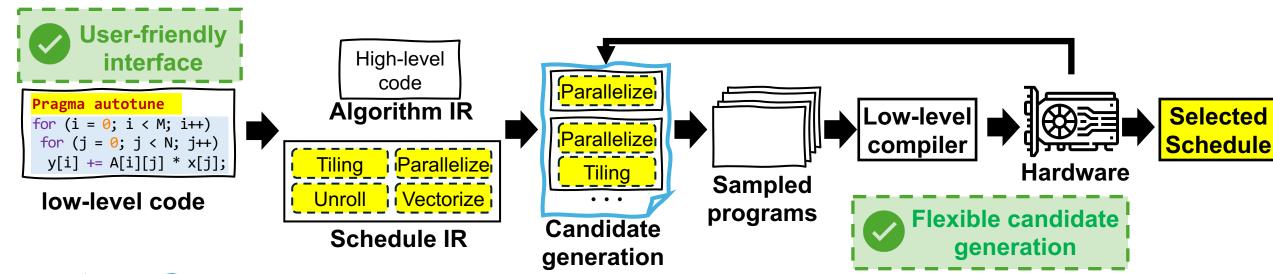






Can we combine the best of both pragma-based and schedule-based approaches to build an autotuning solution for HPC?

→ HYPERF: End-to-End Autotuning Framework for HPC





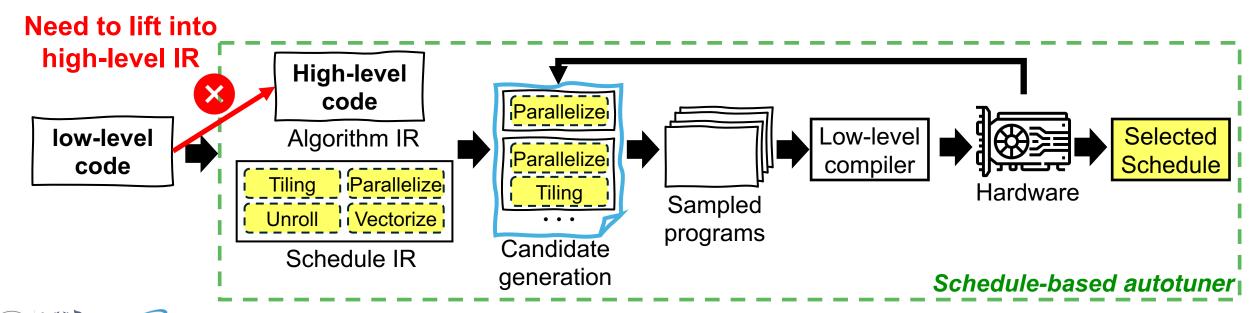




Key Challenges

1. Bridging the abstraction gap between HPC loops and algorithm IR

 Translating low-level programs into algorithm IRs, enabling schedule-based autotuning





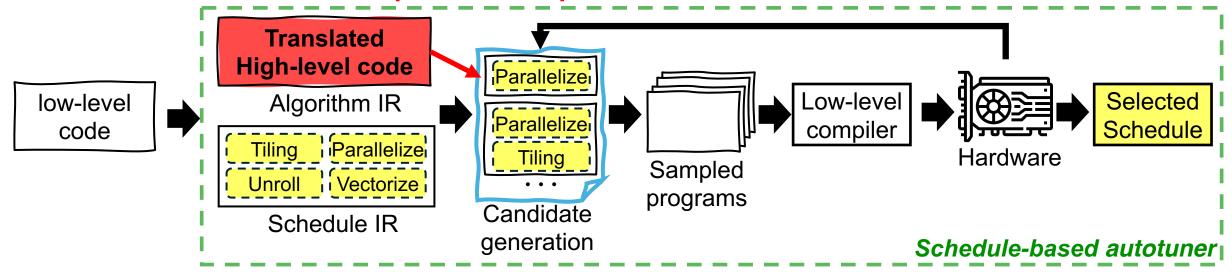
Key Challenges

1. Bridging the abstraction gap between HPC loops and algorithm IR

2. Handling structural differences between HPC and DL loop

Schedule-based autotuner cannot directly handle complex and arbitrary HPC loop structures

Need to restructure complex HPC loops!







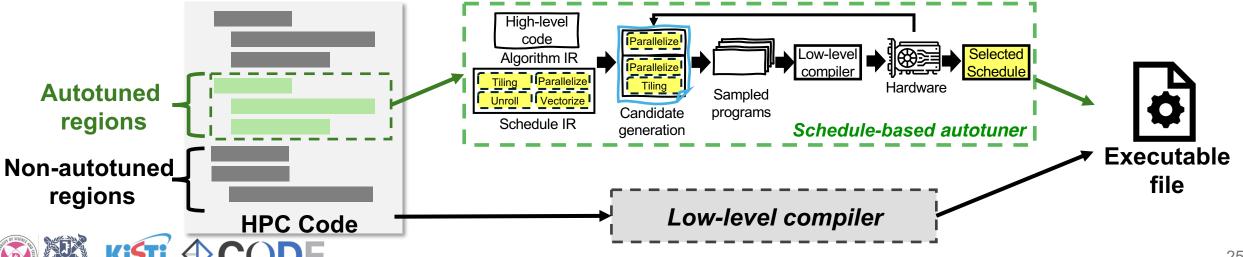


Key Challenges

1. Bridging the abstraction gap between HPC loops and algorithm IR

2. Handling structural differences between HPC and DL loops

- 3. Integrating compilation flows for a smooth user experience
 - Compile and optimize both autotuned and non-autotuned regions



- 1. Bridging the abstraction gap between HPC loops and algorithm IR
- → OpenMP C/C++-to-TIR translator that recovers high-level semantics to enable Schedule-based autotuning

- 2. Handling structural differences between HPC and DL loop
- → TVM-HPC applies TIR canonicalization and expands the autotuning scope to support arbitrary HPC loop structures

- 3. Integrating compilation flows for a smooth user experience
- → Autotuning driver replaces autotuned loops with outlined calls and compiles the remaining code



We propose HYPERF, an end-to-end HPC autotuning framework that combines user-friendly pragma-based interfaces with schedule-based autotuning to achieve flexible and efficient optimization



HYPERF achieves up to 103.5× speedup over baseline OpenMP, with an average of 6.1× over prior HPC autotuners and 4.2× over polyhedral compilers



Outline

Introduction & Motivation

Background

HYPERF

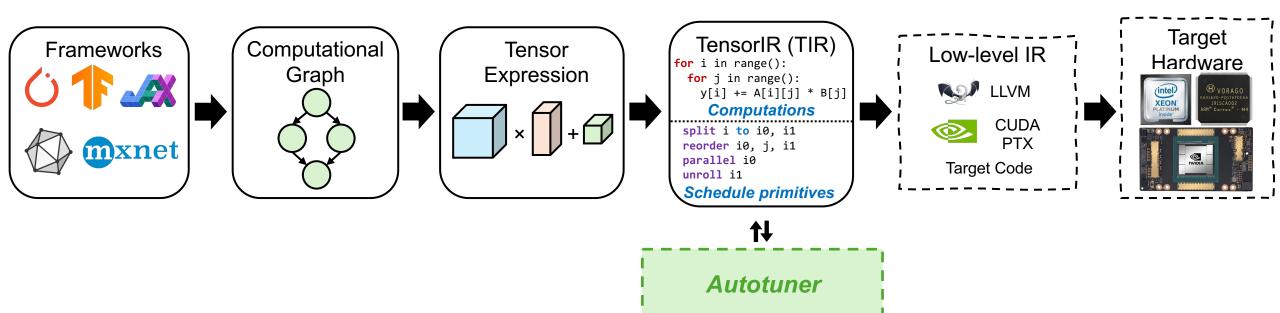
- Overview
- OpenMP C/C++ Autotuning Driver
- TVM-HPC

Evaluation Results





 A DL compiler that uses internal IR layers and an autotuner to optimize models for deployment on diverse hardware



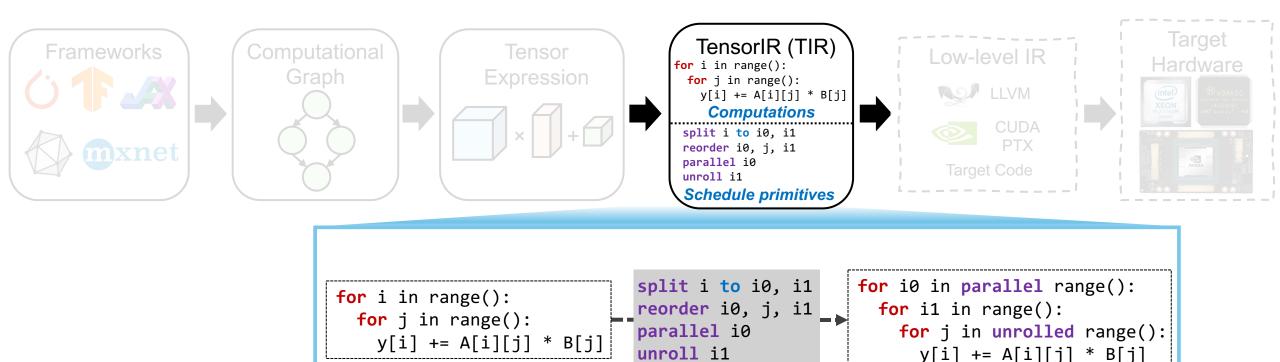








• TensorIR (TIR) separates the algorithm from the schedule, enabling flexible tensor operations



Schedule primitives

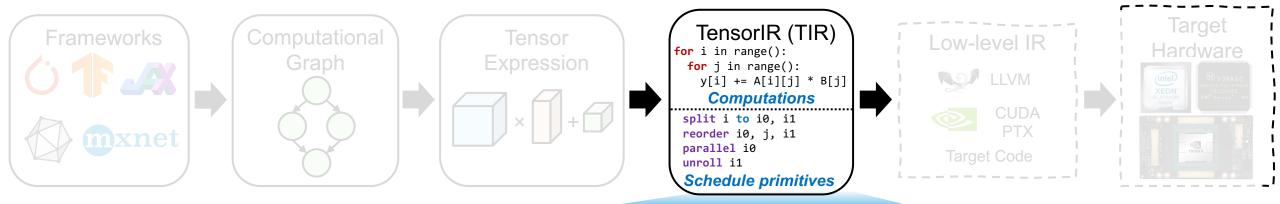


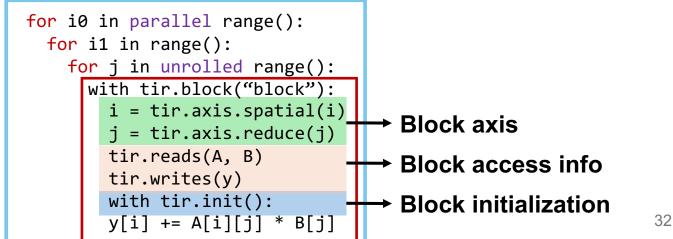






- TIR blocks define computations and data within loops, separating the loop structure from computation
- Block includes key info: axis, data access, and initialization



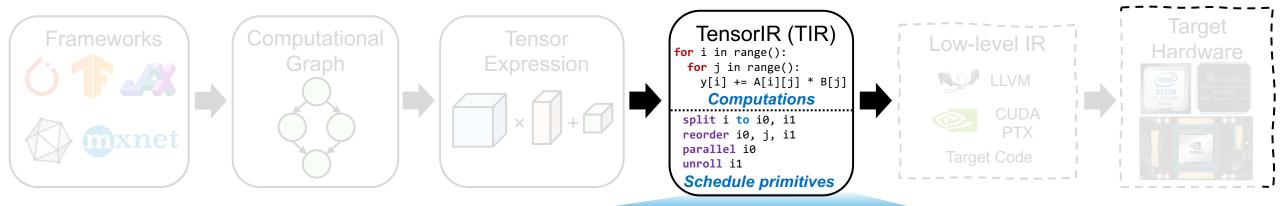


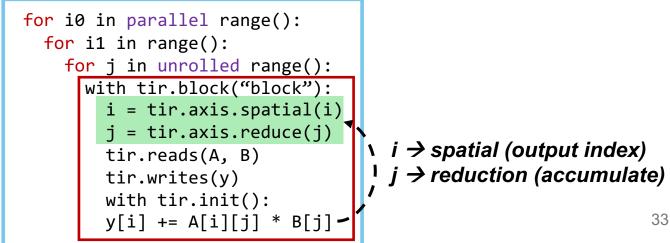






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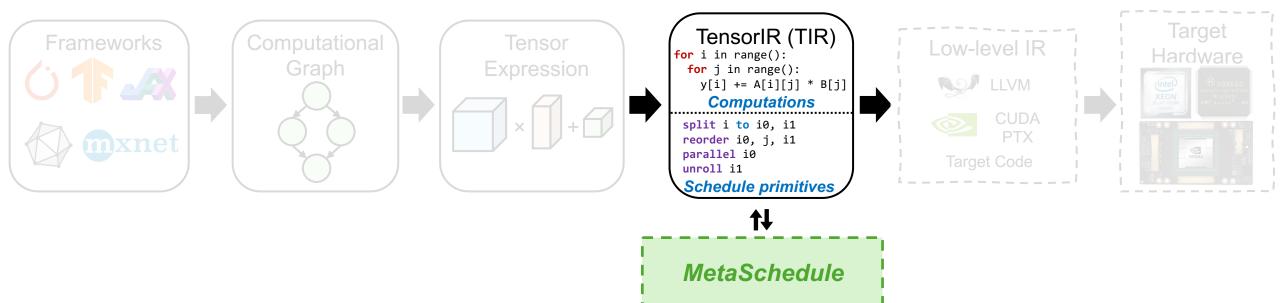








 MetaSchedule autotunes schedule primitives to find the bestperforming versions



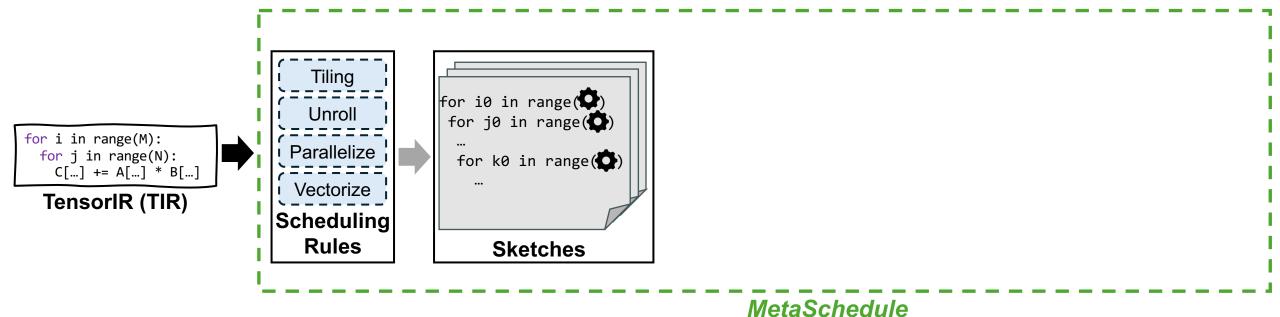








- MetaSchedule autotunes schedule primitives to find the bestperforming versions
 - Generates multiple sketches based on predefined scheduling rules



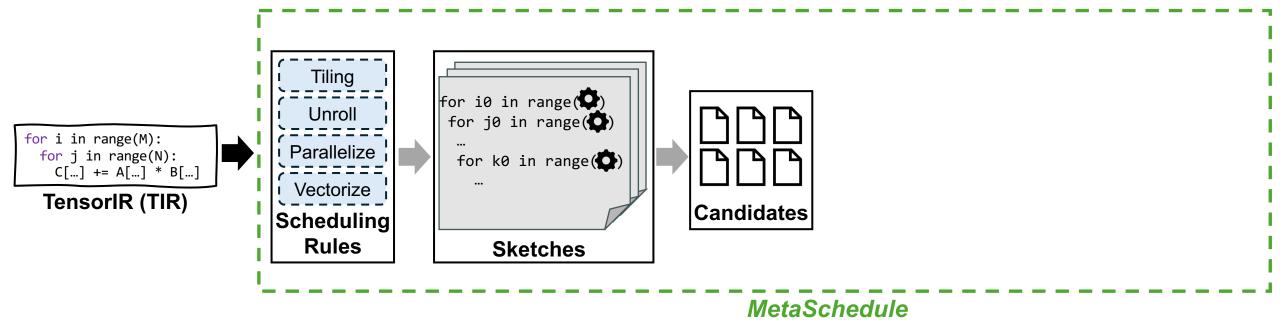








- MetaSchedule autotunes schedule primitives to find the bestperforming versions
 - Produces various candidates by adjusting parameters within these sketches





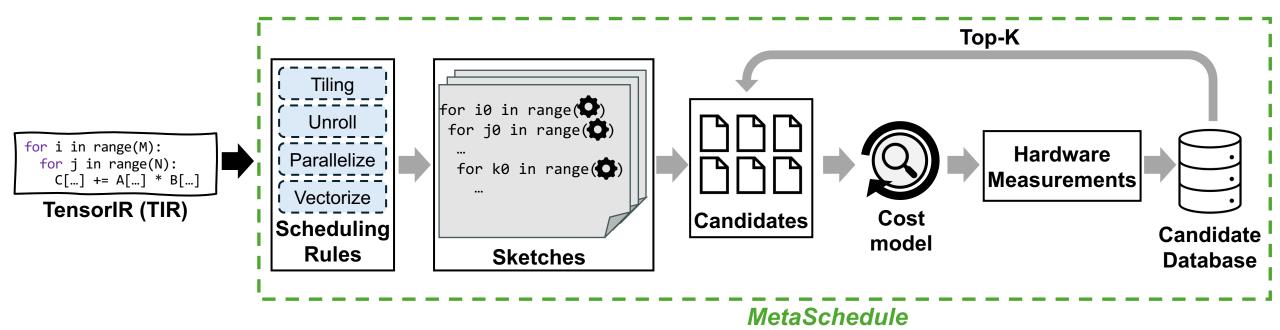






Apache TVM Compiler

- MetaSchedule autotunes schedule primitives to find the bestperforming versions
 - Selects candidates with a cost model, runs them, and finds the best schedule









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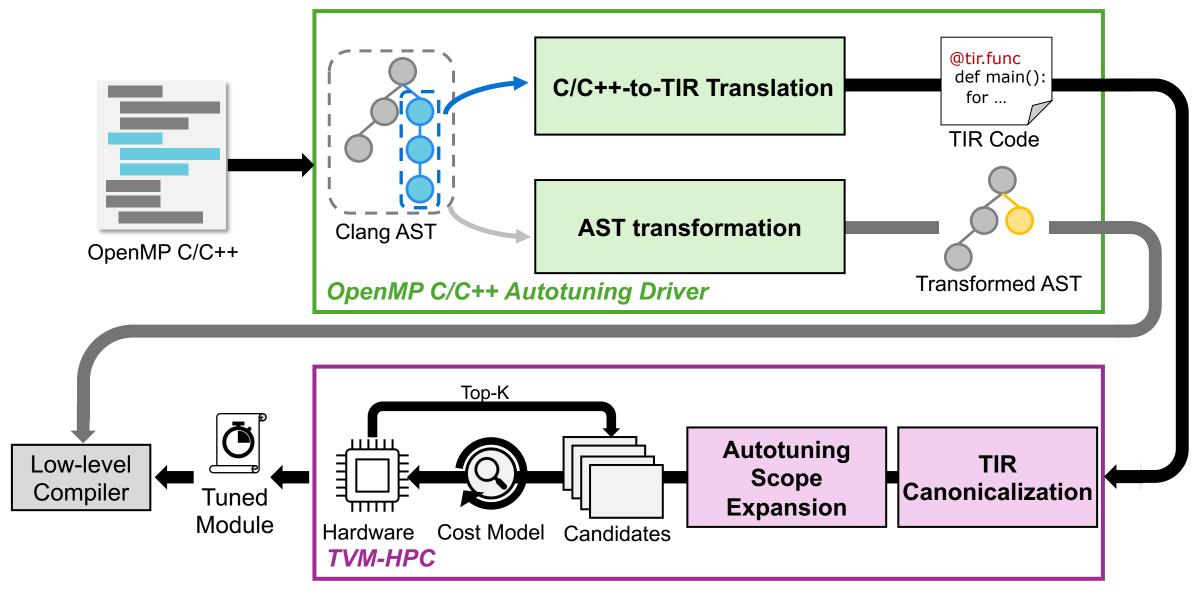
HYPERF

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Evaluation Results





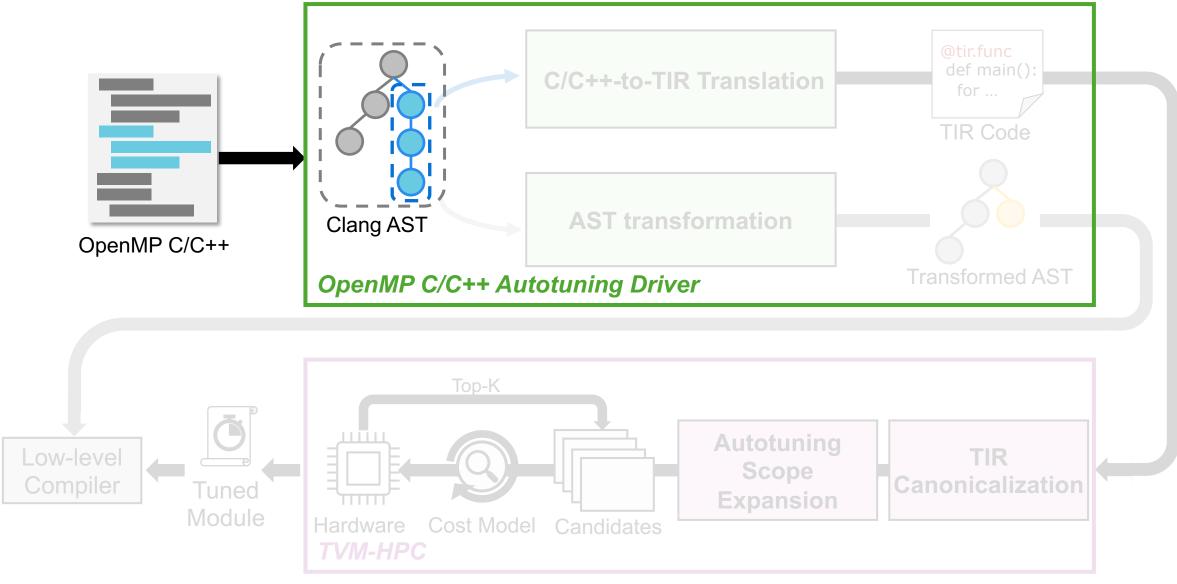










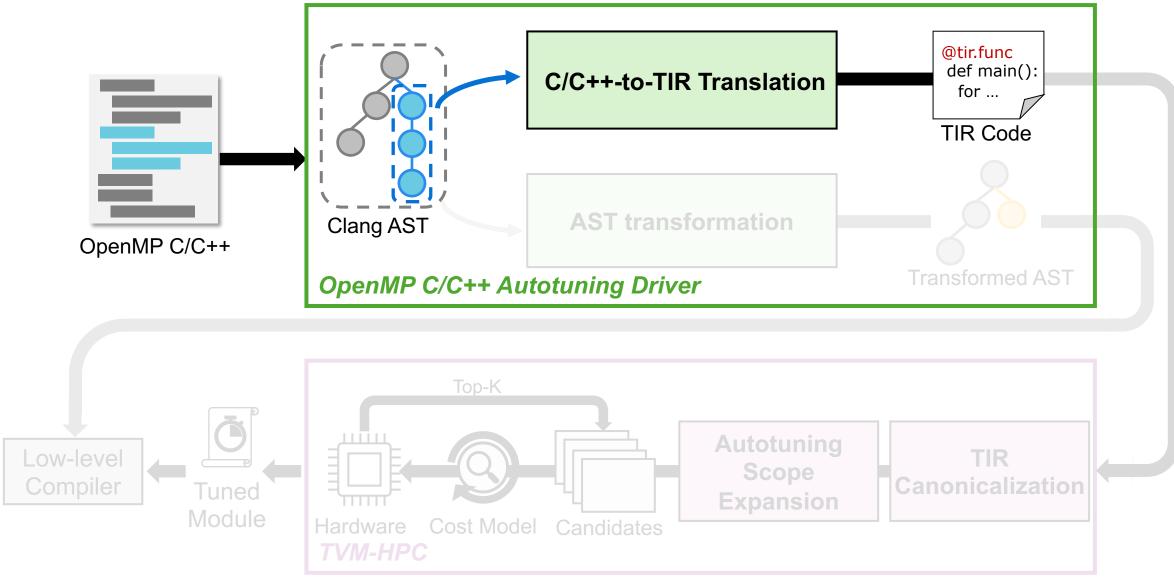










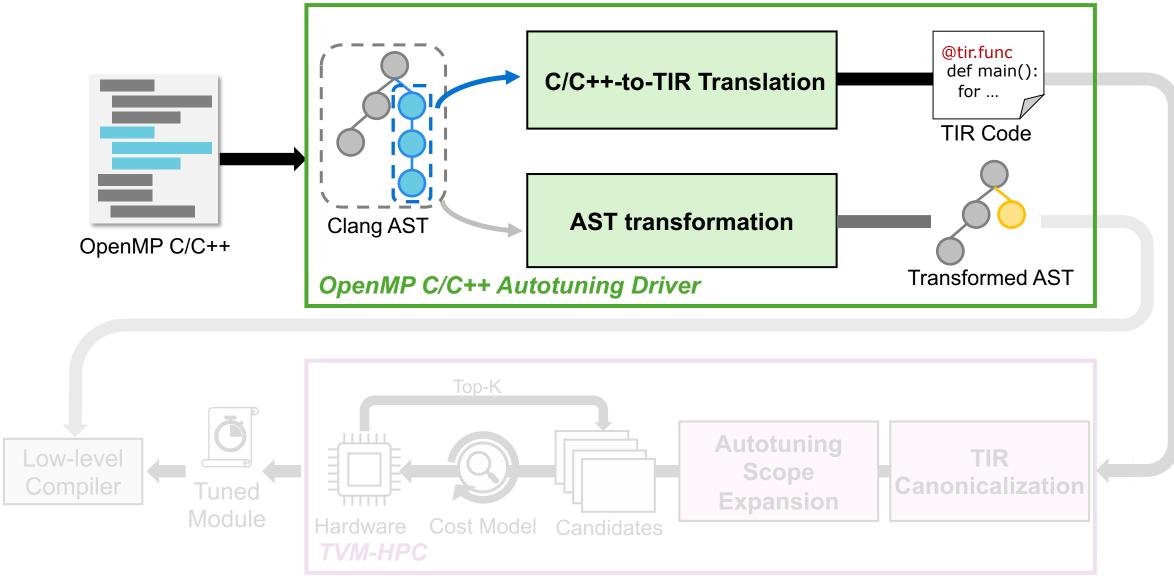










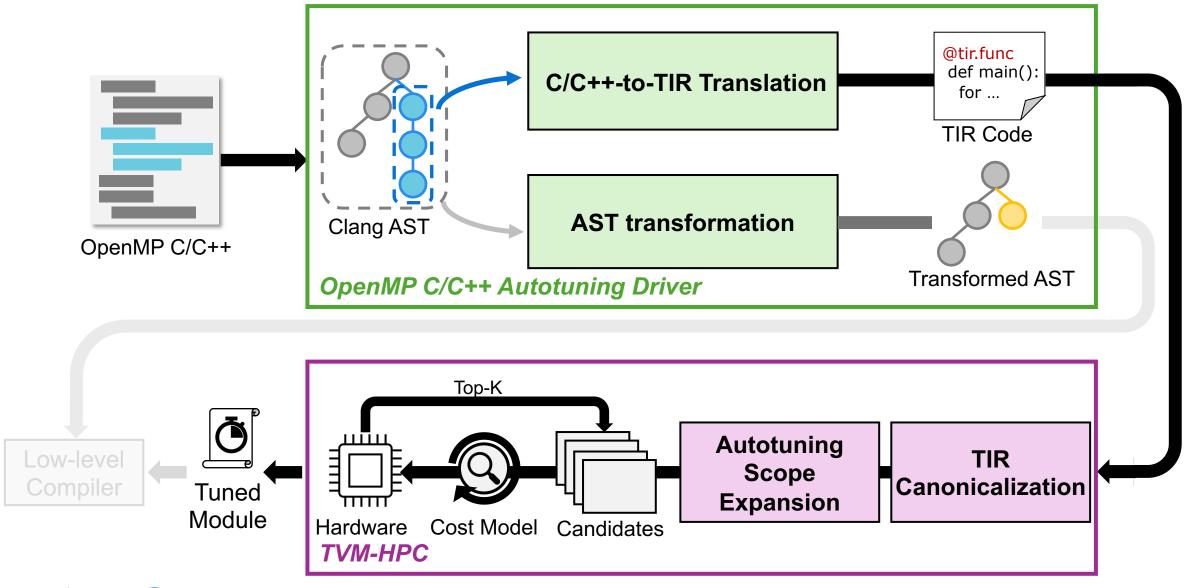










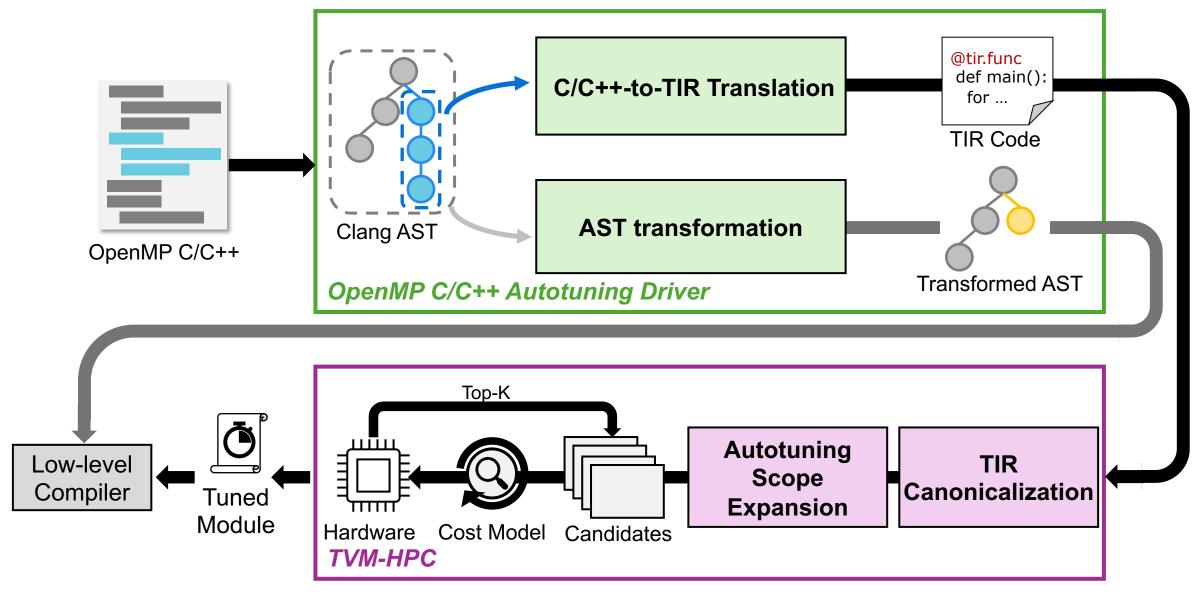




















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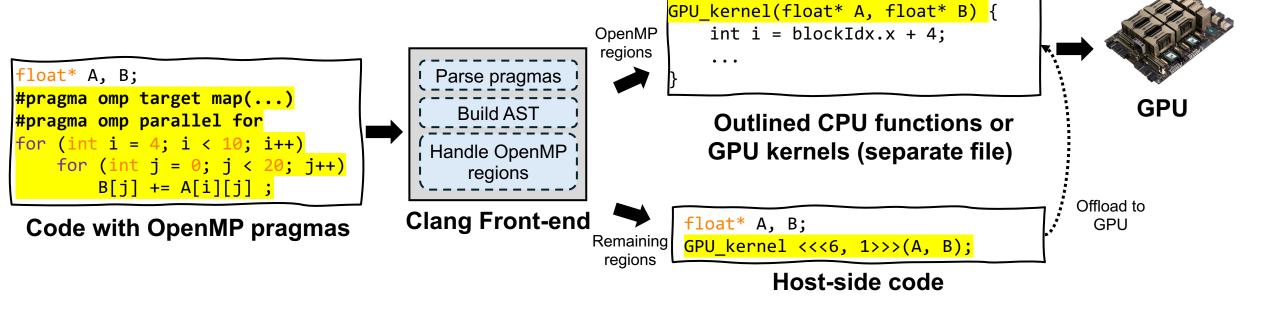
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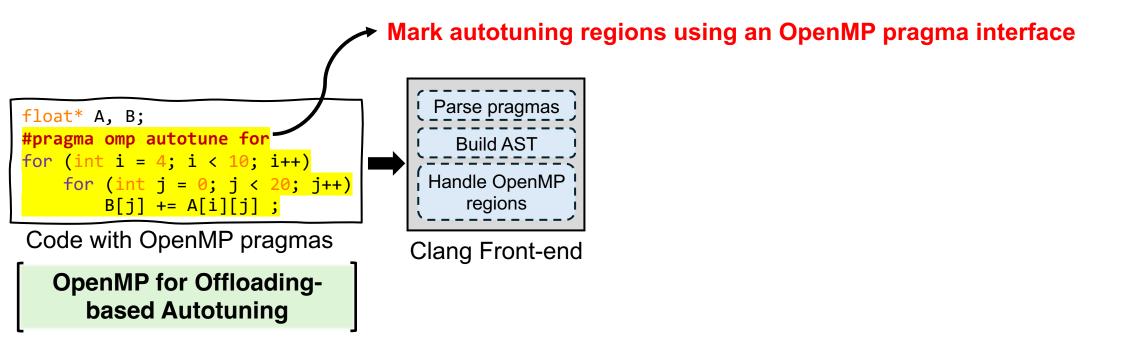


 In an OpenMP compilation, pragmas are handled in the front-end and transformed into outlined functions or GPU kernels for offloading





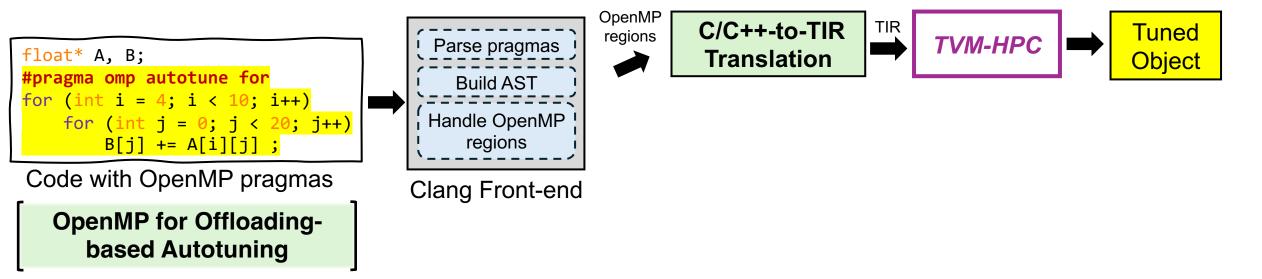
HYPERF extends the OpenMP programming model with an autotune directive and follows a similar compilation flow





HYPERF extends the OpenMP programming model with an autotune directive and follows a similar compilation flow

Translate identified OpenMP regions to TIR and offload to TVM-HPC for tuning



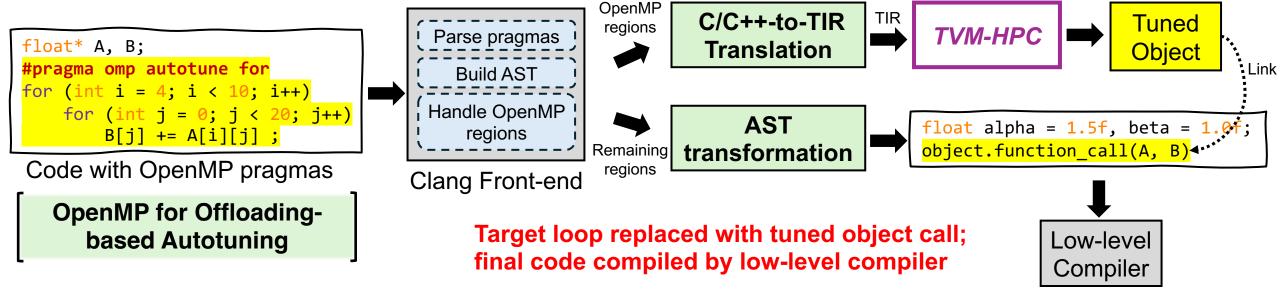








HYPERF extends the OpenMP programming model with an autotune directive and follows a similar compilation flow





• The 'autotune for' directive specifies an autotuning target

Directive and Clause	Syntax	Note
Autotune for Directive	<pre>#pragma omp autotune for [clause[],]</pre>	Specifies loop autotuning via OpenMP pragmas

• map clause: Specifies shared data pointers and array metadata

Directive and Clause	Syntax	Note
Autotune for Directive	<pre>#pragma omp autotune for [clause[],]</pre>	Specifies loop autotuning via OpenMP pragmas
Map Clause	map(map-type: locator-list)	 locator-list: List of arrays with bounds and lengths map-type: Data movement direction



• reduction clause: Specifies reduction variables and sets block axis properties

Directive and Clause	Syntax	Note
Autotune for Directive	<pre>#pragma omp autotune for [clause[],]</pre>	Specifies loop autotuning via OpenMP pragmas
Map Clause	map(map-type: locator-list)	 locator-list: List of arrays with bounds and lengths map-type: Data movement direction
Reduction Clause	reduction(op: list)	op: Specifies the reduction operatorlist: Variables to be reduced across threads



- private clause: Specifies a private variable
- struct_info clause: Provides information on struct members

Directive and Clause	Syntax	Note
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Reduction Clause	reduction(op: list)	op: Specifies the reduction operatorlist: Variables to be reduced across threads
Private Clause	private(list)	list: Thread-private variable
Struct Info Clause	struct_info(struct-list)	struct-list: Structure elements included in the OpenMP region







1. Variable analysis: Identify and analyze variables via AST and clauses to construct a symbol table of TIR variables

OpenMP C/C++ Code #pragma omp autotune for map(tofrom: A[0:10][0:20]...) reduction(+: B[0:20]) for (int i = 4; i < 10; i++) for (int j = 0; j < 20; j++) B[j] += A[i][j];Autotune for directive Mapclause: A[10][20],B[20] Captured Variable Loopvar: i. i Variable: A, B Clang AST

```
Variable: "i", type: int, shape: []
Variable: "j", type: int, shape: []
Variable: "A" — type: array(float), shape: []
Variable: "B" — type: array(float), shape: []

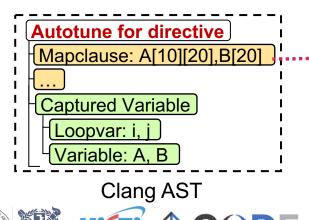
Variables used in the loop body
```

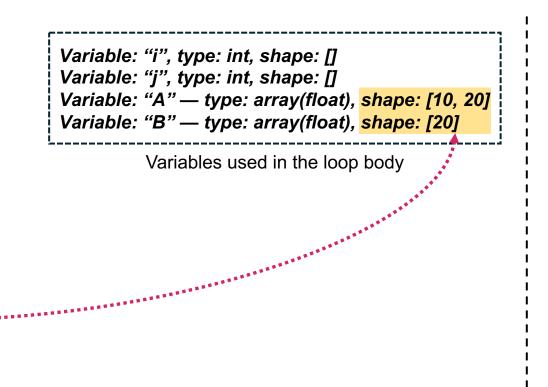
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```





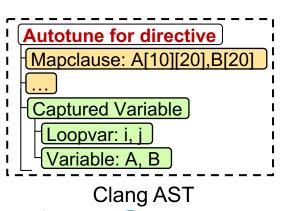


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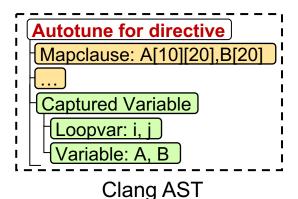
```
Variable: "i", type: int, shape: []
Variable: "j", type: int, shape: []
Variable: "A" — type: array(float), shape: [10, 20]
Variable: "B" — type: array(float), shape: [20]
         Variables used in the loop body
             tir::Var(i,int)
              tir::Var(j,int)
    tir.buffer([10][20], float, A)
       tir.buffer([20], float, B)
          TIR primitive representation
```

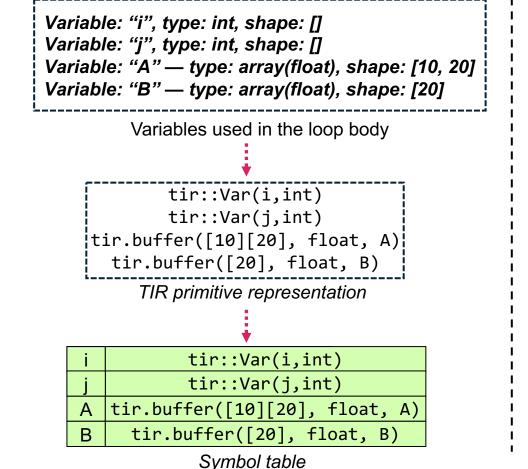
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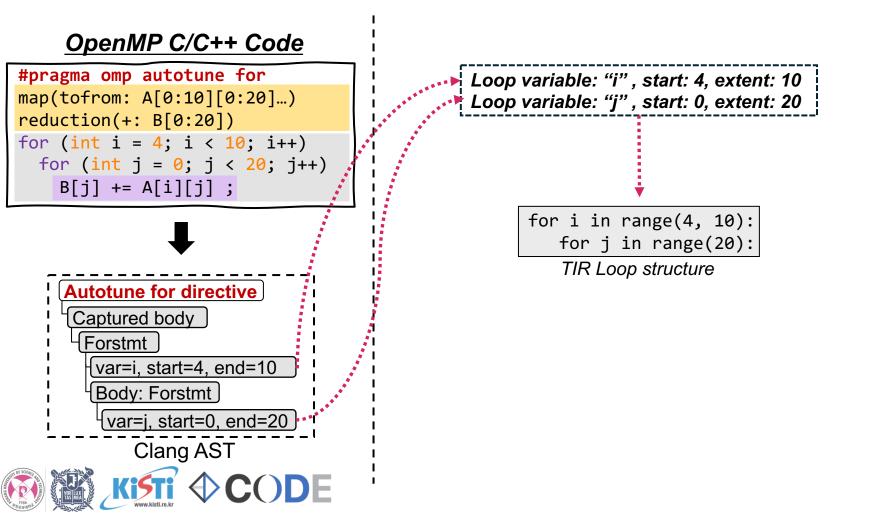
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```







2. Loop structure analysis and generation: Analyze AST loop nodes to generate valid TIR loop headers (variable, start, extent)



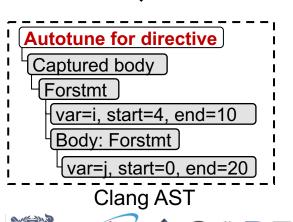
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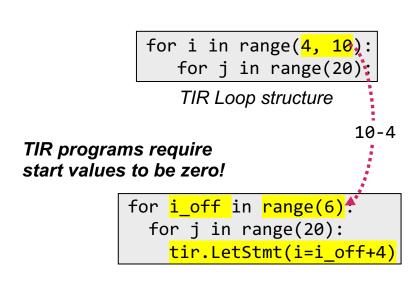
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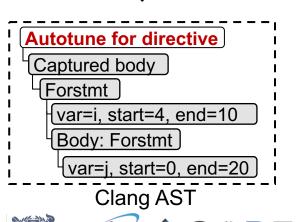
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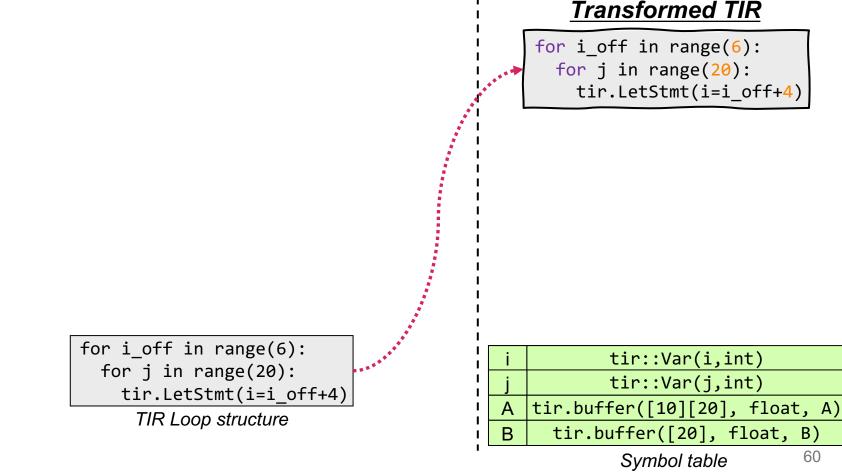
for (int i = 4; i < 10; i++)

B[j] += A[i][j];



for (int j = 0; j < 20; j++)



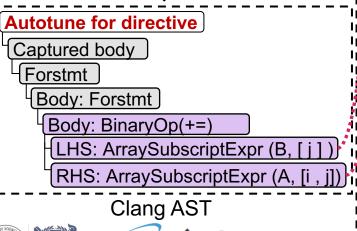


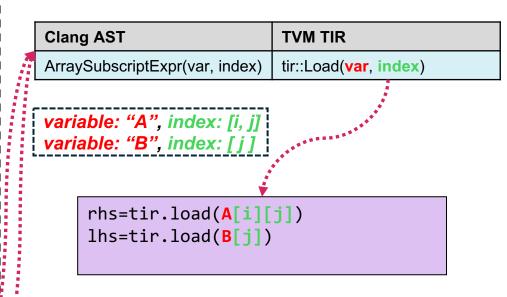
3. Loop body generation: Convert AST nodes to TIR operations based on translation rules

OpenMP C/C++ Code

```
#pragma omp autotune for
map(tofrom: A[0:10][0:20]...)
reduction(+: B[0:20])
for (int i = 4; i < 10; i++)
   for (int j = 0; j < 20; j++)
    B[j] += A[i][j];</pre>
```





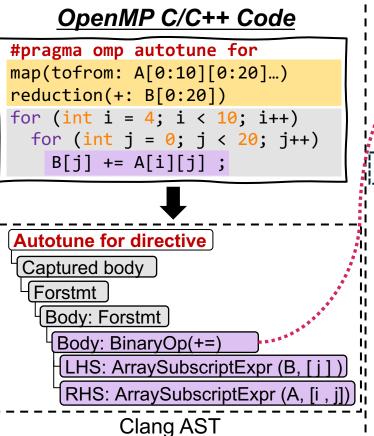


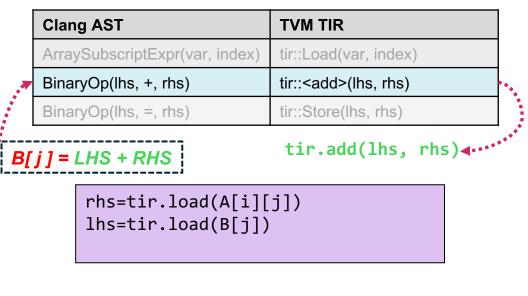
Transformed TIR

for i_off in range(6):
 for j in range(20):
 tir.LetStmt(i=i_off+4)

i	tir::Var(i,int)
j	tir::Var(j,int)
Α	tir.buffer([10][20], float, A)
В	tir.buffer([20], float, B)

3. Loop body generation: Convert AST nodes to TIR operations based on translation rules



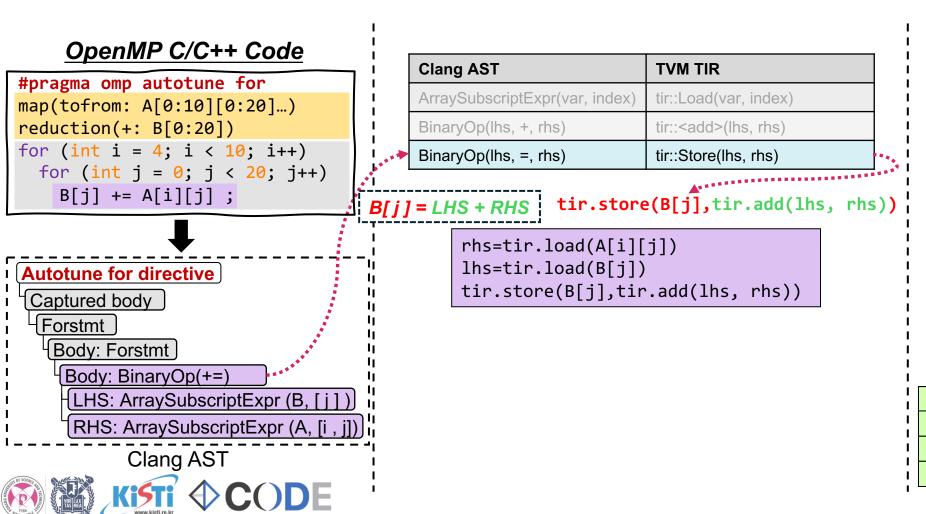


Transformed TIR

for i_off in range(6):
 for j in range(20):
 tir.LetStmt(i=i_off+4)

i	tir::Var(i,int)
j	tir::Var(j,int)
Α	tir.buffer([10][20], float, A)
В	tir.buffer([20], float, B)

3. Loop body generation: Convert AST nodes to TIR operations based on translation rules



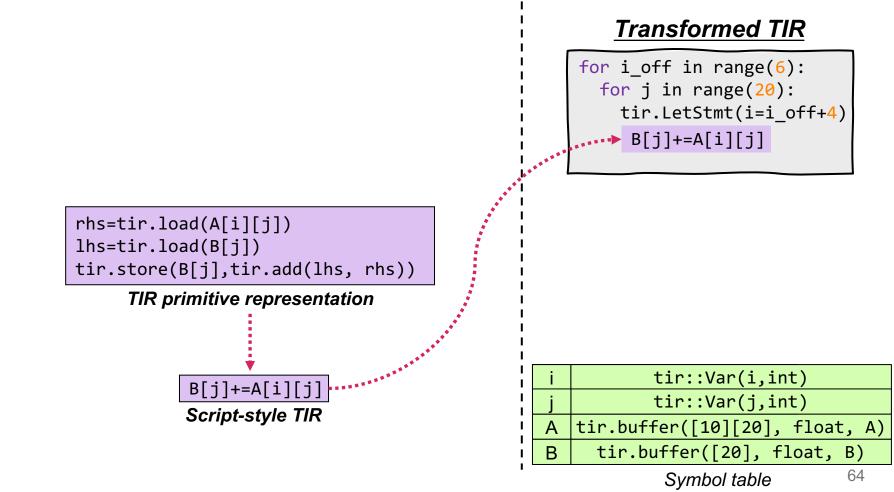
Transformed TIR

for i_off in range(6):
 for j in range(20):
 tir.LetStmt(i=i_off+4)

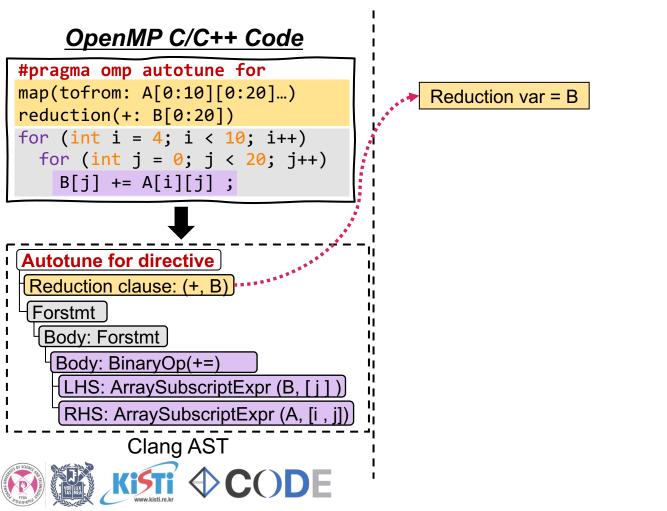
i	tir::Var(i,int)
j	tir::Var(j,int)
Α	tir.buffer([10][20], float, A)
В	tir.buffer([20], float, B)

3. Loop body generation: Convert AST nodes to TIR operations based on translation rules

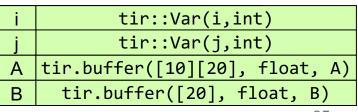
OpenMP C/C++ Code #pragma omp autotune for map(tofrom: A[0:10][0:20]...) reduction(+: B[0:20]) for (int i = 4; i < 10; i++) for (int j = 0; j < 20; j++) B[j] += A[i][j];**Autotune for directive** Captured body Forstmt Body: Forstmt Body: BinaryOp(+=) LHS: ArraySubscriptExpr (B, [i]) RHS: ArraySubscriptExpr (A, [i , j]) Clang AST



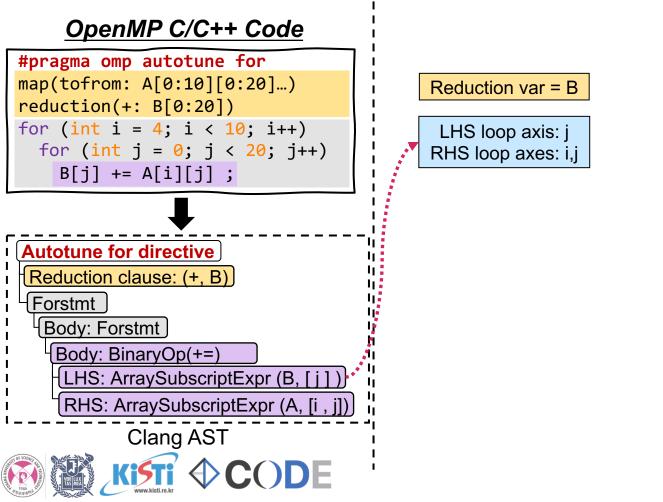
4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis



```
for i_off in range(6):
   for j in range(20):
     tir.LetStmt(i=i_off+4)
     B[j]+=A[i][j]
```



4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis



```
for i_off in range(6):
   for j in range(20):
     tir.LetStmt(i=i_off+4)
     B[j]+=A[i][j]
```

```
i tir::Var(i,int)
j tir::Var(j,int)
A tir.buffer([10][20], float, A)
B tir.buffer([20], float, B)
```

4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis

OpenMP C/C++ Code #pragma omp autotune for map(tofrom: A[0:10][0:20]...) reduction(+: B[0:20]) for (int i = 4; i < 10; i++) for (int j = 0; j < 20; j++) B[j] += A[i][j] ; **Autotune for directive** Reduction clause: (+, B) Forstmt Body: Forstmt Body: BinaryOp(+=) LHS: ArraySubscriptExpr (B, [j] RHS: ArraySubscriptExpr (A, [i , j]) Clang AST

```
Reduction var = B

LHS loop axis: j
RHS loop axes: i,j

Reduction axis = i
Spatial axis = j
```

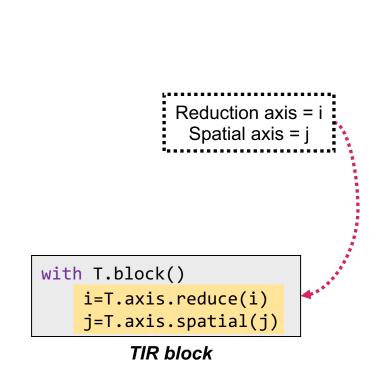
Operation accumulates to buffer B on the 'j' axis, 'i' is identified as the reduction axis

```
for i_off in range(6):
   for j in range(20):
     tir.LetStmt(i=i_off+4)
     B[j]+=A[i][j]
```

```
i tir::Var(i,int)
j tir::Var(j,int)
A tir.buffer([10][20], float, A)
B tir.buffer([20], float, B)
```

4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis

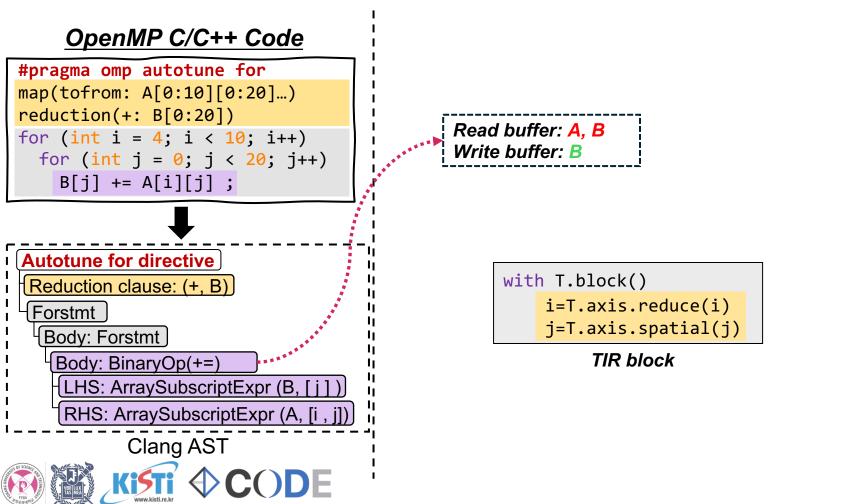
OpenMP C/C++ Code #pragma omp autotune for map(tofrom: A[0:10][0:20]...) reduction(+: B[0:20]) for (int i = 4; i < 10; i++) for (int j = 0; j < 20; j++) B[j] += A[i][j];**Autotune for directive** Reduction clause: (+, B) Forstmt Body: Forstmt Body: BinaryOp(+=) LHS: ArraySubscriptExpr (B, [j]) RHS: ArraySubscriptExpr (A, [i , j]) Clang AST



```
for i_off in range(6):
   for j in range(20):
     tir.LetStmt(i=i_off+4)
     B[j]+=A[i][j]
```

```
i tir::Var(i,int)
j tir::Var(j,int)
A tir.buffer([10][20], float, A)
B tir.buffer([20], float, B)
```

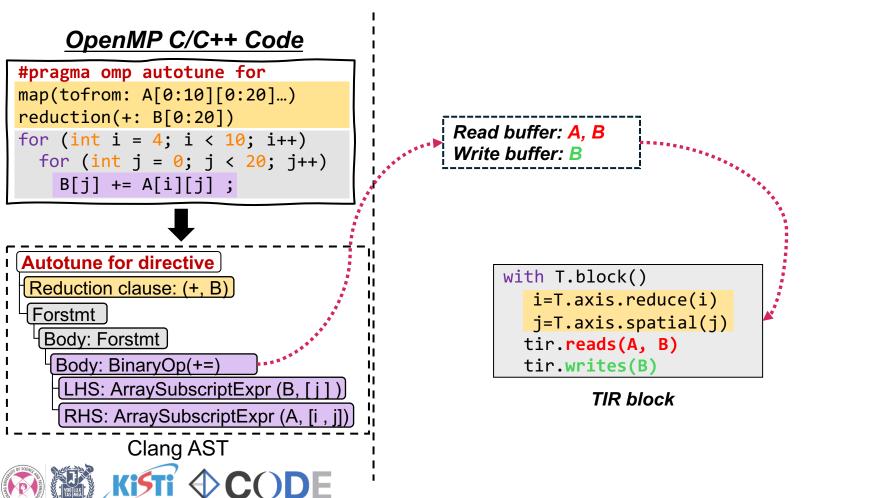
4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis



```
for i_off in range(6):
   for j in range(20):
     tir.LetStmt(i=i_off+4)
     B[j]+=A[i][j]
```

```
i tir::Var(i,int)
j tir::Var(j,int)
A tir.buffer([10][20], float, A)
B tir.buffer([20], float, B)
```

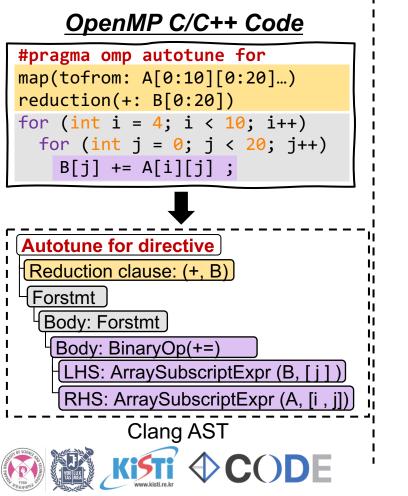
4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis

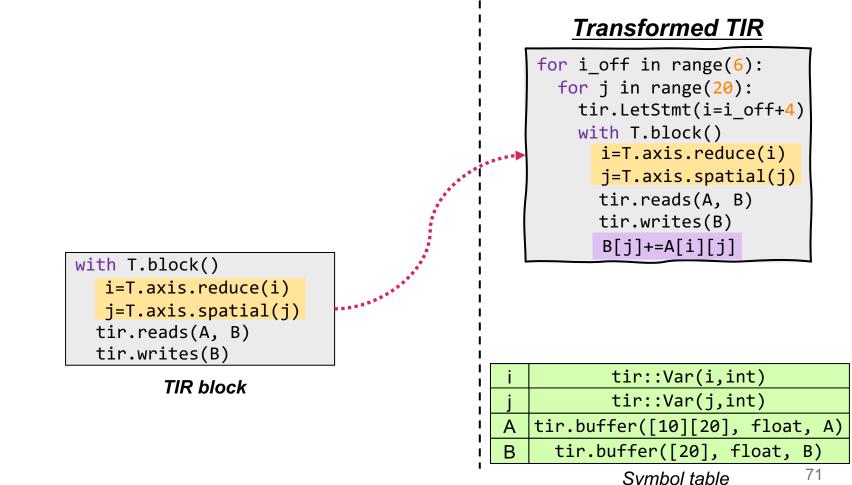


```
for i_off in range(6):
   for j in range(20):
     tir.LetStmt(i=i_off+4)
     B[j]+=A[i][j]
```

```
i tir::Var(i,int)
j tir::Var(j,int)
A tir.buffer([10][20], float, A)
B tir.buffer([20], float, B)
```

4. TIR block generation: Define block axes (spatial/reduce) and data access info using reduction clauses and AST analysis

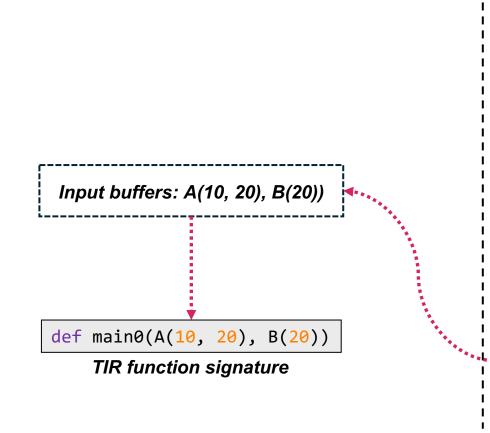




5. TIR function generation: Build the final TIR function using the generated body and input variables

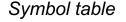
OpenMP C/C++ Code

```
#pragma omp autotune for
map(tofrom: A[0:10][0:20]...)
reduction(+: B[0:20])
for (int i = 4; i < 10; i++)
  for (int j = 0; j < 20; j++)
   B[j] += A[i][j];</pre>
```



```
for i_off in range(6):
    for j in range(20):
        tir.LetStmt(i=i_off+4)
    with T.block()
        i=T.axis.reduce(i)
        j=T.axis.spatial(j)
        tir.reads(A, B)
        tir.writes(B)
        B[j]+=A[i][j]
```

i	i tir::Var(i,int)	
j	tir::Var(j,int)	
Α	<pre>tir.buffer([10][20], float, A)</pre>	
В	<pre>tir.buffer([20], float, B)</pre>	



OpenMP C/C++-to-TIR Translation

5. TIR function generation: Build the final TIR function using the generated body and input variables

OpenMP C/C++ Code

```
#pragma omp autotune for
map(tofrom: A[0:10][0:20]...)
reduction(+: B[0:20])
for (int i = 4; i < 10; i++)
  for (int j = 0; j < 20; j++)
   B[j] += A[i][j];</pre>
```

Transformed TIR def main0(A(10, 20), B(20)) for i off in range(6): for j in range(20): tir.LetStmt(i=i off+4) with T.block() i=T.axis.reduce(i) j=T.axis.spatial(j) tir.reads(A, B) tir.writes(B) B[j]+=A[i][j] def main0(A(10, 20), B(20)) TIR function signature



Outline

Introduction & Motivation

Background

HYPERF

- Overview
- OpenMP C/C++ Autotuning Driver
- TVM-HPC

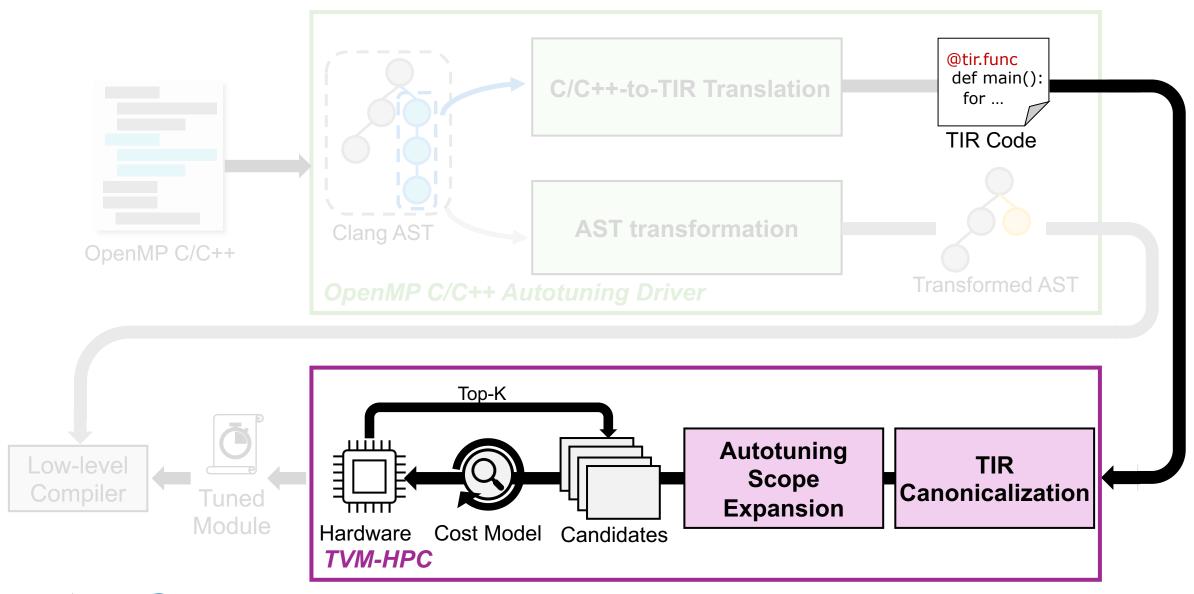
Evaluation Results







Overview





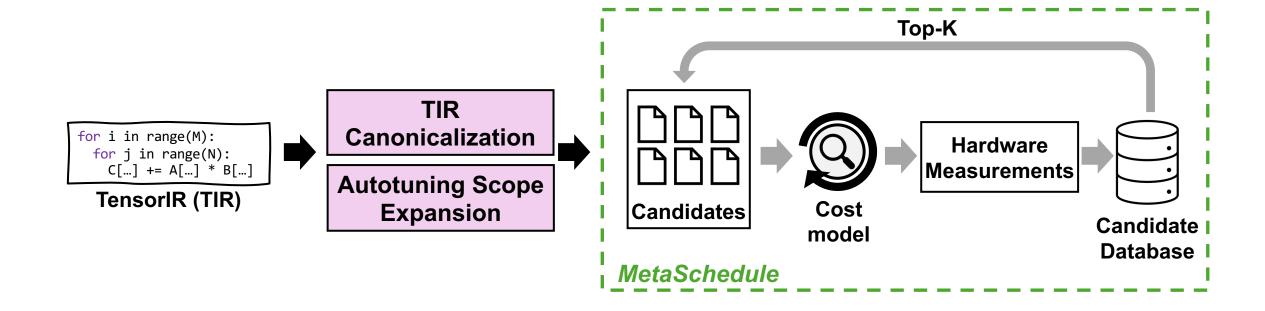






TVM-HPC

- TVM-HPC builds on TVM autotuning but extends it in two ways:
 - TIR canonicalization
 - Autotuning scope expansion









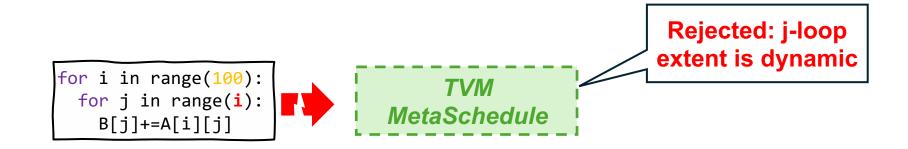


- TVM only triggers autotuning when the TIR meets legality and profitability constraints
- → TIR canonicalization passes ensure the TIR generated by the autotuning driver is compatible with MetaSchedule autotuning



Identify autotuning constraints and canonicalize the TIR

Only static loop extents are supported











Identify autotuning constraints and canonicalize the TIR

- Only static loop extents are supported
 - → Consolidate dynamic loop bounds into static extents

```
for i in range(100):
    for j in range(i):
        B[j]+=A[i][j]
for i in range(100):
    for j in range(99):
        B[j]+=A[i][j]
```

Propagate outer bounds to give inner loops static max extents





Identify autotuning constraints and canonicalize the TIR

- Only static loop extents are supported
 - → Consolidate dynamic loop bounds into static extents

```
for i in range(100):
for j in range(\mathbf{i}):
B[j]+=A[i][j]
for i in range(100):
B[j]+=A[i][j]
for i in range(\mathbf{99}):
B[j]+=A[i][j]
B[j]+=A[i][j]
```

Add tir.where to prevent inner loops from exceeding original extents



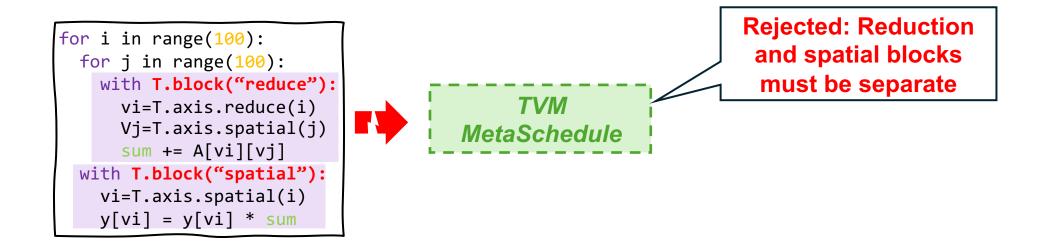






Identify autotuning constraints and canonicalize the TIR

Reduction blocks must be separate from other TIR blocks









Identify autotuning constraints and canonicalize the TIR

- Reduction blocks must be separate from other TIR blocks
 - → Separate spatial and reduction loops

```
for i in range(100):
for i in range(100):
                                         for j in range(100):
  for j in range(100):
                                           with T.block("reduce"):
    with T.block("reduce"):
                                             vi=T.axis.reduce(i)
                                             Vj=T.axis.spatial(j)
      vi=T.axis.reduce(i)
      Vj=T.axis.spatial(j)
                                             sum += A[vi][vj]
      sum += A[vi][vj]
 with T.block("spatial"):
                                       for i in range(100):
    vi=T.axis.spatial(i)
                                         with T.block("spatial"):
                                           vi=T.axis.spatial(i)
    y[vi] = y[vi] * sum
                                           y[vi] = y[vi] * sum
```

Each block is split into a separate loop for independent execution and optimization







Identify autotuning constraints and canonicalize the TIR

- Reduction blocks must be separate from other TIR blocks
 - → Separate spatial and reduction loops

```
for i in range(100):
                                                                              for i in range(100):
for i in range(100):
                                                                                for j in range(100):
                                         for j in range(100):
                                           with T.block("reduce"):
                                                                                  with T.block("reduce"):
  for j in range(100):
                                                                                    vi=T.axis.reduce(i)
    with T.block("reduce"):
                                             vi=T.axis.reduce(i)
                                                                                    Vj=T.axis.spatial(j)
                                             Vj=T.axis.spatial(j)
      vi=T.axis.reduce(i)
     Vj=T.axis.spatial(j)
                                                                                    sum expand[vi] += A[vi][vj]
                                             sum += A[vi][vj]
      sum += A[vi][vj]
                                                                              for i in range(100):
 with T.block("spatial"):
                                       for i in range(100):
    vi=T.axis.spatial(i)
                                         with T.block("spatial"):
                                                                                with T.block("spatial"):
                                                                                  vi=T.axis.spatial(i)
                                           vi=T.axis.spatial(i)
   y[vi] = y[vi] * sum
                                                                                  y[vi] = y[vi] * sum expand[vi
                                           y[vi] = y[vi] * sum
```

Expand reduction buffers to keep values after loop fission







Identify autotuning constraints and canonicalize the TIR

Buffer indices must be defined using loop variables

```
for i in range(99):
    tmp = i + 1
    C[tmp] = A[tmp] * B[tmp]
Rejected: Buffer indices
    not loop-dependent

MetaSchedule
```







Identify autotuning constraints and canonicalize the TIR

- Buffer indices must be defined using loop variables
 - → Replace temporary variables in buffer indices

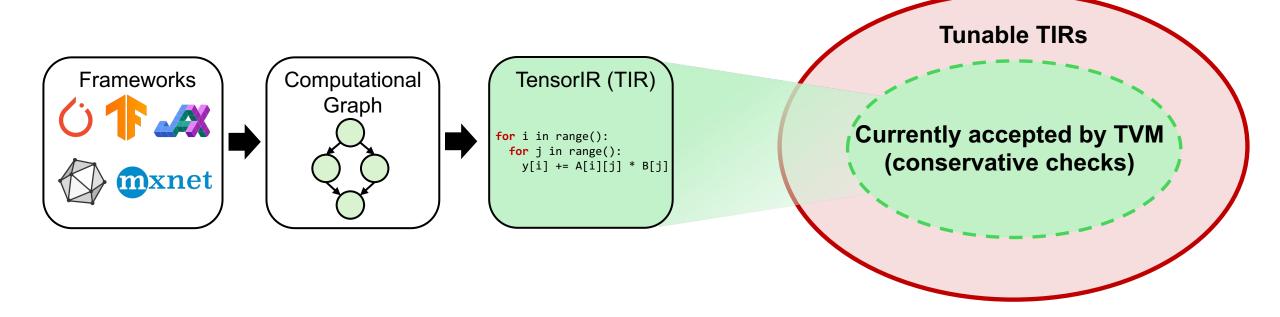
```
for i in range(99):
    tmp = i + 1
    C[tmp] = A[tmp] * B[tmp]
for i in range(99):
    C[i + 1] = A[i + 1] * B[i + 1]
```

Rewrite temp vars to make buffer indices depend only on loop vars



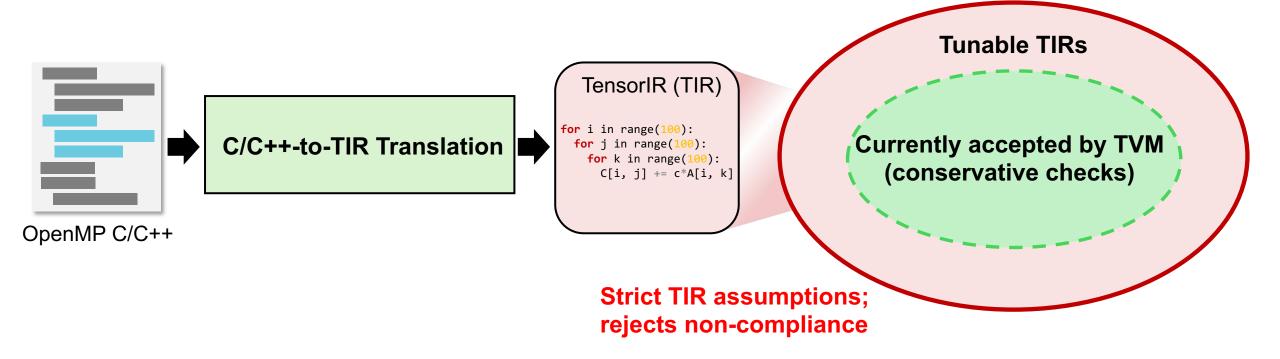


- Original TVM autotuner assumes TIRs from TVM front-end
 - Adding extra safety checks before generating schedules to ensure correct optimization and stability



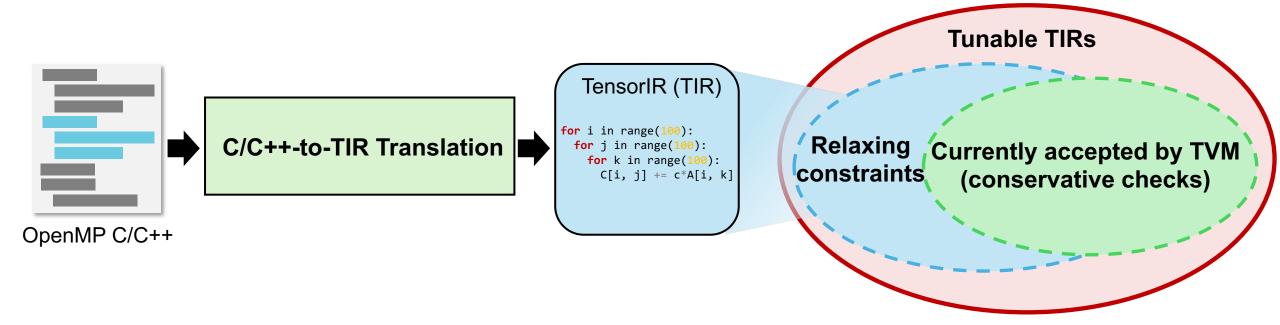


These checks may reject valid TIRs from HYPERF's front-end





- These checks may reject valid TIRs from HYPERF's front-end
- Relaxing constraints enables more autotuning opportunities
 - Relax block dependency constraint
 - Relax constant buffer access range requirement (refer to the paper)





- Relax Block Dependency Constraint
 - TVM front-end (e.g., DL graphs) ensures strict dependency constraints
 - Translated TIR may introduce WAR dependencies by reusing read buffers

```
for i in range(100):
    for j in range(100):
        with T.block("block 1"):
        sum[i, j] += A[i, j] * B[j]
    for i in range(100):
        for j in.range(100):
        with T.block("block 2"):
        A[i, j] = sum[i, j]

WAR dependency
```



- Relax Block Dependency Constraint
 - TVM front-end (e.g., DL graphs) ensures strict dependency constraints
 - Translated TIR may introduce WAR dependencies by reusing read buffers

```
for i in range(100):
    for j in range(100):
        with T.block("block 1"):
        sum[i, j] += A[i, j] * B[j]

for i in range(100):
    for j in range(100):
        with T.block("block 2"):
        A[i, j] = sum[i, j]
```

Block 2 runs after Block 1 completes



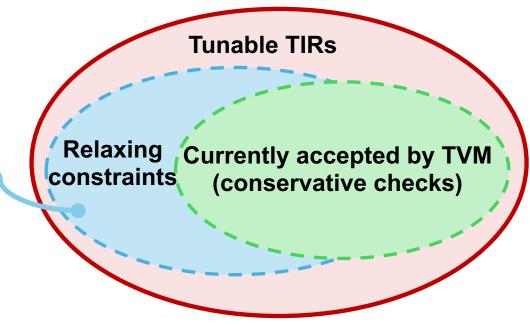




- Relax Block Dependency Constraint
 - TVM front-end (e.g., DL graphs) ensures strict dependency constraints
 - Translated TIR may introduce WAR dependencies by reusing read buffers
 - → Relax block dependency constraint to enable tuning even with WAR dependencies

```
for i in range(100):
    for j in range(100):
        with T.block("block 1"):
        sum[i, j] += A[i, j] * B[j]

for i in range(100):
    for j in range(100):
        with T.block("block 2"):
        A[i, j] = sum[i, j]
```





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Methodology

Evaluated Benchmarks

- PolyBench: gemm, 2mm, 3mm, syrk, syr2k, gesummv, mvt, atax, gemver, bicg, convolution-2d, convolution-3d, durbin
 - Input sizes: small, standard, and large, as defined by PolyBench
- Rodinia: hotspot, particlefilter, srad

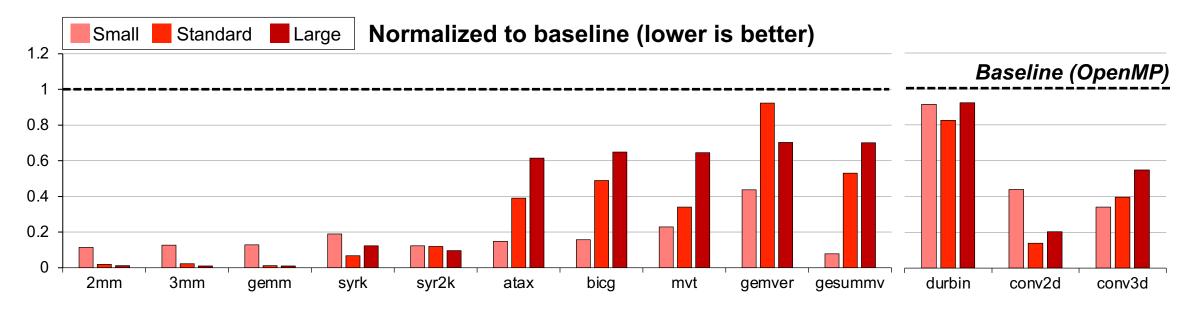
Experiment Environment

Dual-socket Intel Xeon Gold 6426Y CPU with 512GB of DDR5-4800 memory

Experiment Configurations

Configuration	Optimization Method
Baseline	OpenMP versions
Pluto/Polly	Polyhedral compilers
ytopt/OpenTuner	Prior HPC autotuners (pragma-based)
HYPERF	Our proposed autotuning solution





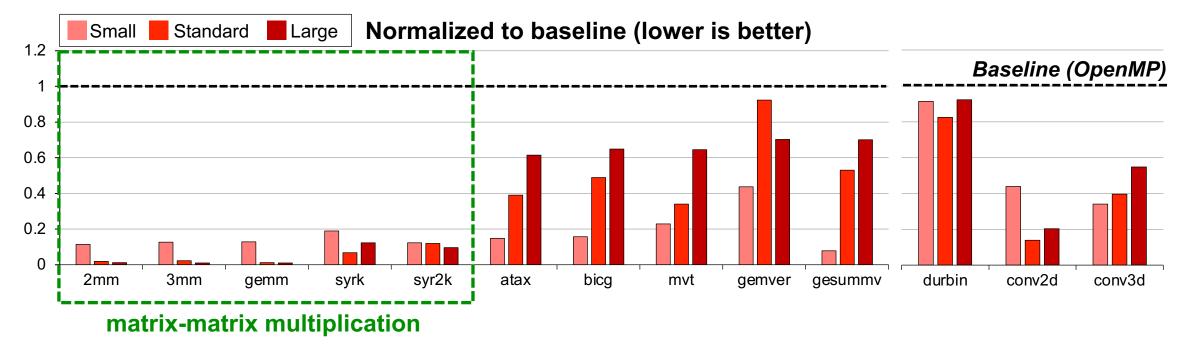
- HYPERF achieves speedups of up to 103.5× (5.5× on average) over baseline
- → Driver effectively translates pragma C/C++ to TIR; TVM-HPC boosts performance via autotuning





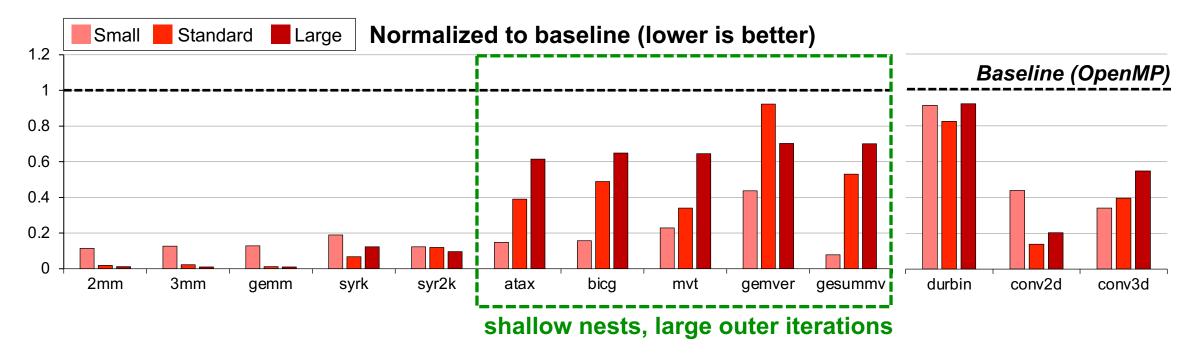






- TVM autotuner **focuses on tensor loops**, like matrix-matrix multiplication, and tunes them using **tiling and unrolling**
- Larger inputs improve data reuse and cache efficiency, boosting performance

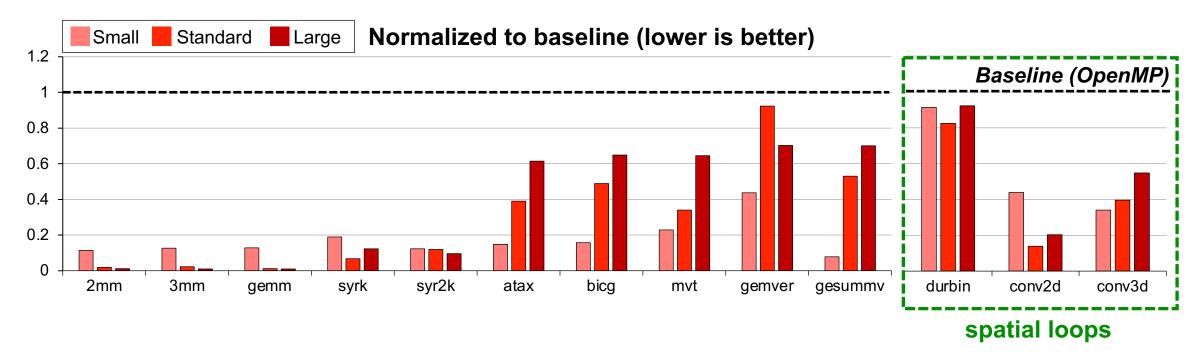




- Performance gains mainly come from parallelization and vectorization
- These benchmarks involve matrix-vector computations with data reuse only in vector accesses







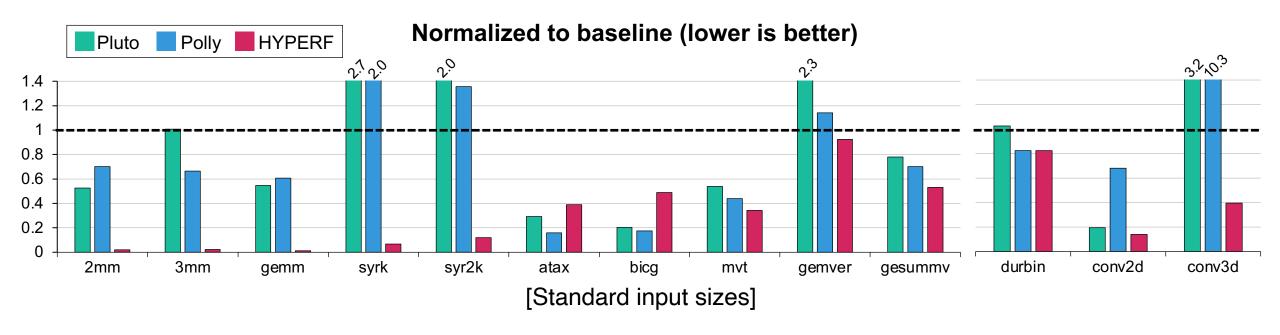
- Since baseline already parallelizes and vectorizes well, extra gains were less visible
- For conv-2d, HYPERF uses wider vector instructions (e.g., ZMM), achieving up to 7.2× speedup over baseline







HYPERF vs. Pluto/Polly



• **HYPERF** outperforms **Pluto** and **Polly** by **4**× and **4.3**× on average (up to 49.4× and 54.8×), respectively

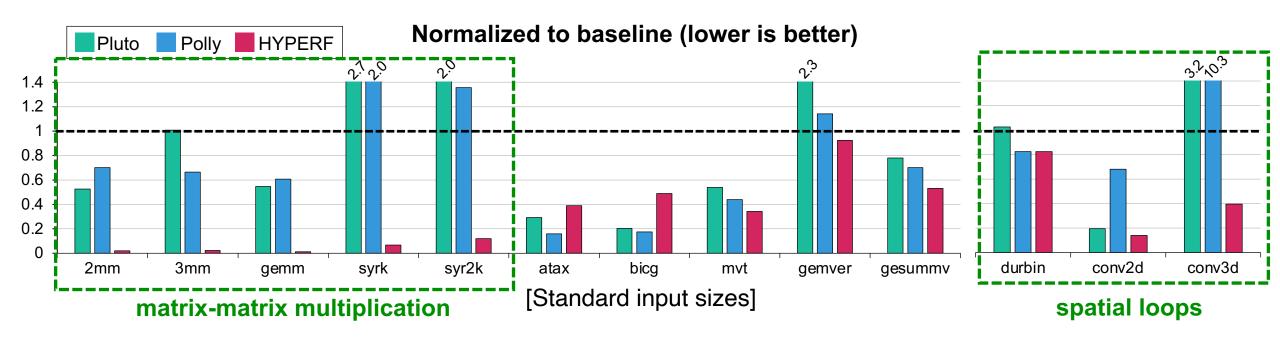








HYPERF vs. Pluto/Polly



- While Pluto and Polly also optimize loops, HYPERF is faster thanks to empirical tuning, multi-level tiling, and loop collapsing
- Pluto and Polly utilize only a fixed tile size, which limits reuse and parallelism

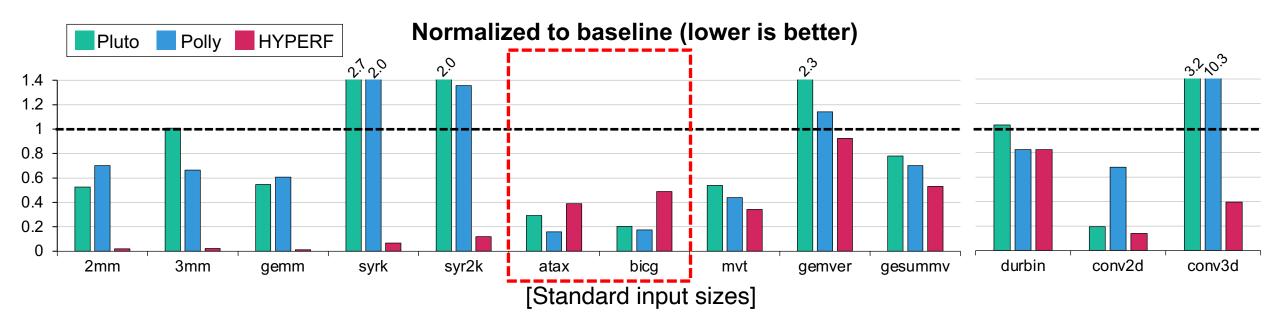








HYPERF vs. Pluto/Polly



- Pluto and Polly outperform HYPERF on certain benchmarks (e.g., atax, bicg) by applying loop interchange to improve spatial locality
- HYPERF (built on TVM) currently does not support loop interchange

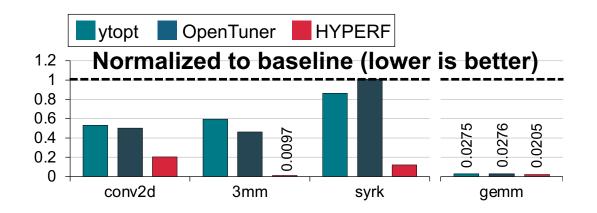








HYPERF vs. ytopt/OpenTuner



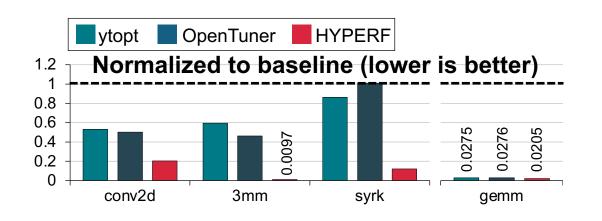
• HYPERF outperforms ytopt and OpenTuner by 6.2× and 6× on average, respectively

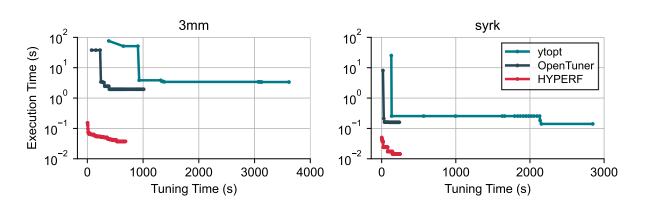






HYPERF vs. ytopt/OpenTuner





- HYPERF outperforms ytopt and OpenTuner by 6.2× and 6× on average, respectively
- HYPERF reduces autotuning time, converging 7.8× faster than ytopt and 1.2× faster than OpenTuner on average
 - Explores a wide search space with a learned cost model









Code snippets of the 3mm kernel

```
#pragma omp parallel for private(j, k)
for (i = 0; i < 2000; i++)
  for (j = 0; j < 2000; j++){
    C[i][j] = 0;
    for (k = 0; k < 2000; ++k)
        C[i][j] += A[i][k] * B[k][j];
}</pre>
```

Baseline(OpenMP)

```
#pragma omp parallel for schedule(static,4)
private(j,k) num_threads(32)
for (i = 0; i < 2000; i++)
  for (j = 0; j < 2000; j++){
    C[i][j] = 0;
    for (k = 0; k < 2000; ++k)
    C[i][j] += A[i][k] * B[k][j];
}</pre>
```

ytopt-optimized version

```
with T.block("root"):
  T.block attr("parallel": 1024, "unroll": 512, "vectorize": 64)
 for i 0 in range(1):
                                tiling, thread parallelization,
  for j 0 in range(10):
                                vectorization, and loop unrolling
   for i 1 in range(1000):
    for j 1 in range(2):
      for k 0 in range(400):
       for i 2 in range(1):
        for j 2 in range(100):
         for k 1 in range(5):
          for i 3 in range(2):
           for j 3 in range(1):
            with T.block("reduction block: C"):
             i = T.axis.spatial(2000, i 0 % 10 * 200 + i 1 * 20 + i 2)
             j = T.axis.spatial(2000, j_0 // 10 * 80 + j_1 * 16 + j_2)
             k = T.axis.reduce(2000, k 0 * 50 + k 1)
             C[i, j] = C[i, j] + A[i, k] * B[k, j]
```

HYPERF-optimized version

HYPERF generates flexible and powerful candidates using high-level TVM IR



Summary

HYPERF

- Bridges the abstraction gap by translating OpenMP-style C/C++ to TIR, integrating existing HPC codes into advanced autotuning
- Proposes TIR canonicalization and autotuning scope expansion, enabling highly flexible candidate generation and powerful optimization for complex HPC loops
- Proposes an autotuning driver that cleanly integrates outlined loops, ensuring seamless compilation
- Provides an end-to-end HPC autotuning framework combining familiar OpenMPstyle programmability with robust, efficient schedule-based optimization
- Achieves superior performance, outperforming existing HPC autotuners and polyhedral compilers











Code available at: https://github.com/SNU-CODElab/HYPERF

HYPERF: End-to-End Autotuning Framework for High-Performance Computing

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