RAMMER: Enabling Holistic Deep Learning Compiler Optimizations with rTasks

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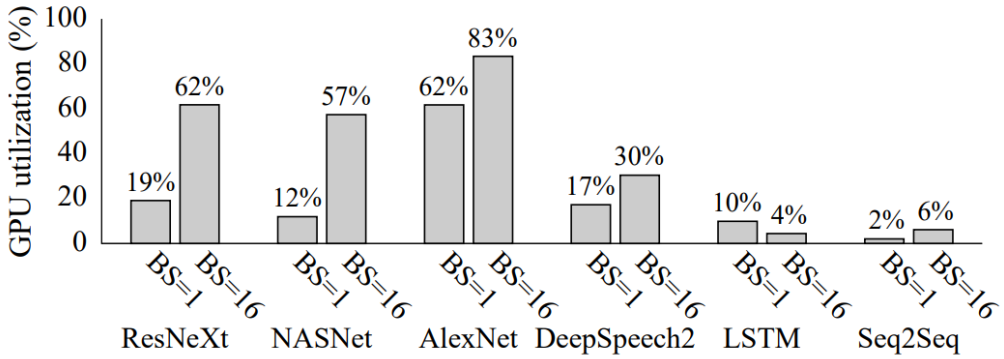
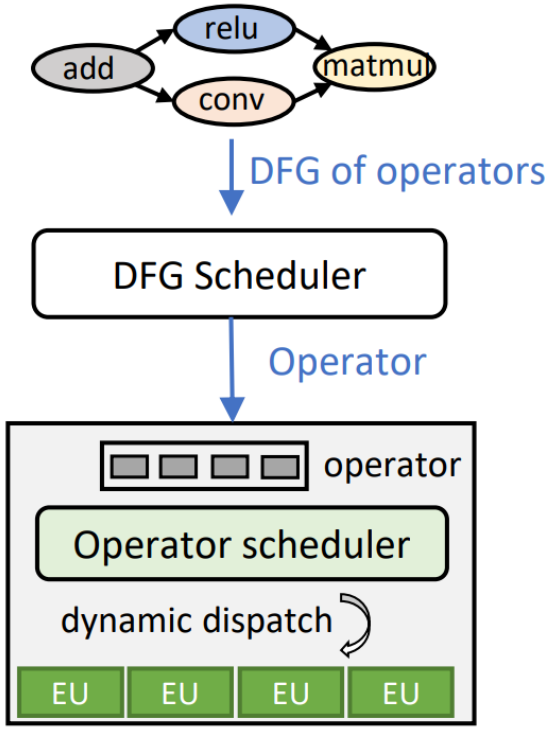
Presented by Tianrong Zhang

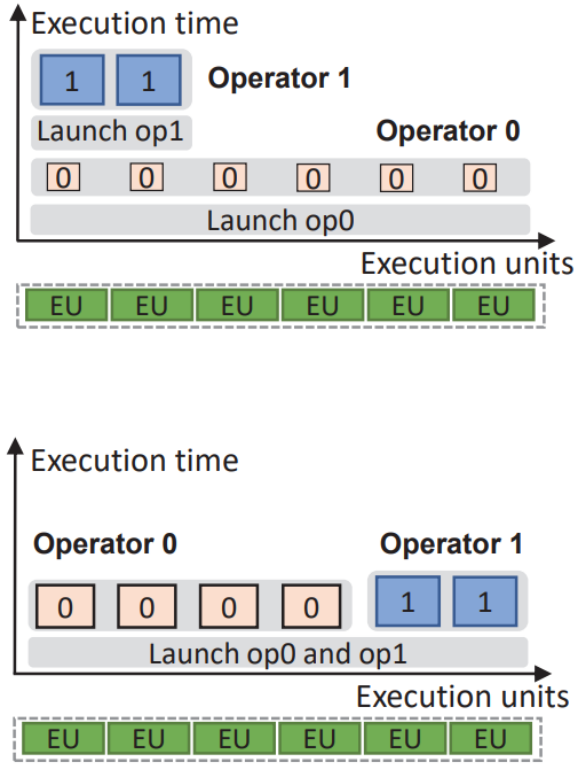
Motivations

- DNNs are often vastly parallelizable
  - Accelerators: GPU, FPGA, etc.
  - However, accelerators aren't fully utilized



  - Intra- and Inter- operator parallelism

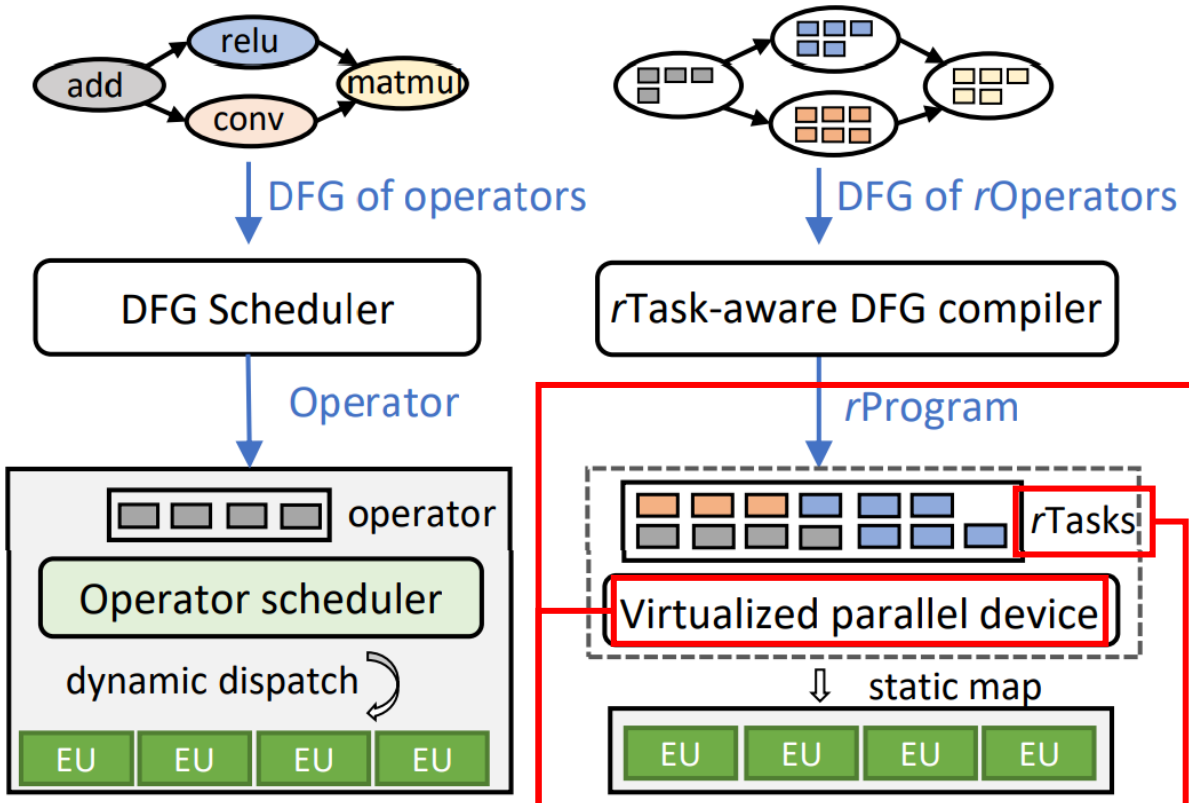




Challenges

- The operator implementations and their profiling details are opaque to DFG schedulers
  - Include operator implementations in DFG
  - Run profiler to gather details of each operation implementation
  - Use opensource libraries though less efficient in some cases
- The accelerators do not provide interface for software to manage the underlying scheduling
  - Define software required interfaces
  - Replace hardware scheduling with software
- Expensive for in time compilation
  - Apply only to freezed and static graph so that compilation can be done ahead of time

Compiler Workflow



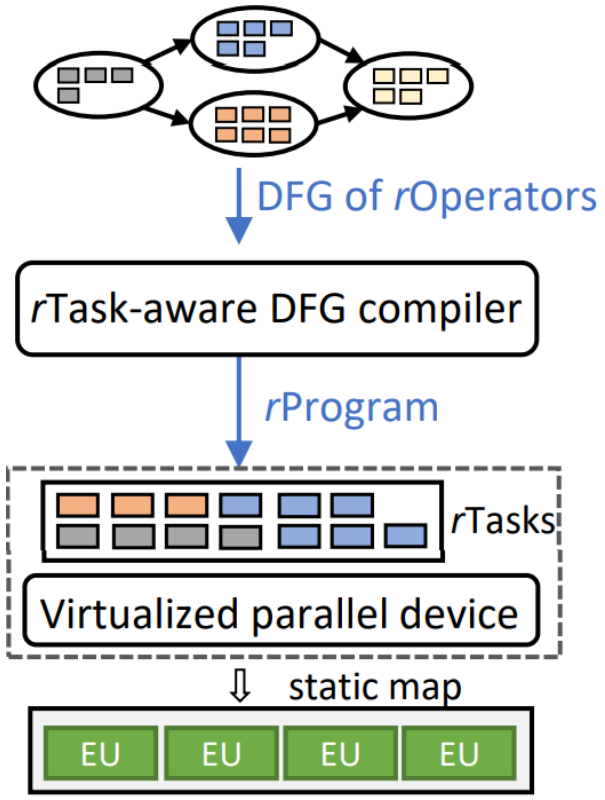

```
1  interface Operator { void compute(); };
2  interface rOperator {
3    void compute_rtask(size_t rtask_id);
4    size_t get_total_rtask_num();
5  };
```

```
1  __device__ void matmul_rTask(float *A, float *B,
2      float *C, size_t rtask_id) {
3    size_t tile_x = rtask_id / (M/32);
4    size_t tile_y = rtask_id % (N/32);
5    size_t i = threadIdx.x/32 + tile_x*32;
6    size_t j = threadIdx.x%32 + tile_y*32;
7    C[i][j] = 0;
8    for (size_t k = 0; k < K; k++)
9      C[i][j] += A[i][k] * B[k][j];
10 }
11
12 class MatmulROperator {
13   __device__ void compute_rtask(size_t rtask_id){
14     matmul_rTask(input0,input1,output0,rtask_id);}
15   size_t get_total_rtask_num(){return M/32*N/32);}
16 };
```

Expose potential profiling detail of each minimum job

Expose managing interface of hardware scheduling

Compiler Workflow



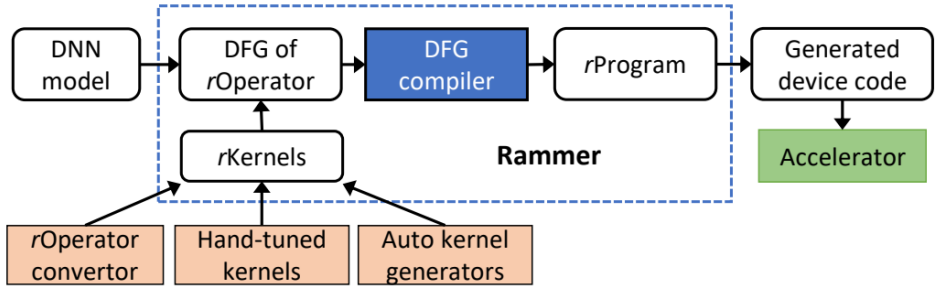

```
1  // config: <<<(vEU_size,1,1), (vEU#,1,1)>>>
2  __global__ void vdevice_run() {
3    if (Get_vEU_Id() == 0) { // vEU 0
4      MatmulrTaskOp.compute_rtask(0);
5      MatmulrTaskOp.compute_rtask(1);
6      // wait the rTask on vEU 1 with order=3
7      BarrierTask({<1, 3>}).compute_rtask();
8      Conv2DrTaskOp.compute_rtask(0);
9    }
10   else if (Get_vEU_Id() == 1) { // vEU 1
11     for (auto i : 4)
12       RelurTaskOp.compute_task(i);
13     // wait the rTask on vEU 0 with order=1
14     BarrierTask({<0, 1>}).compute_rtask();
15     Conv2DrTaskOp.compute_rtask(1);
16   }
17
```

wait mechanism

Store a step array in *r*Program's shared memory to keep track of of completed *r*Tasks.

persistent threadblock { vEu1, vEu2

Scheduling Strategy



Algorithm 1: Wavefront Scheduling Policy

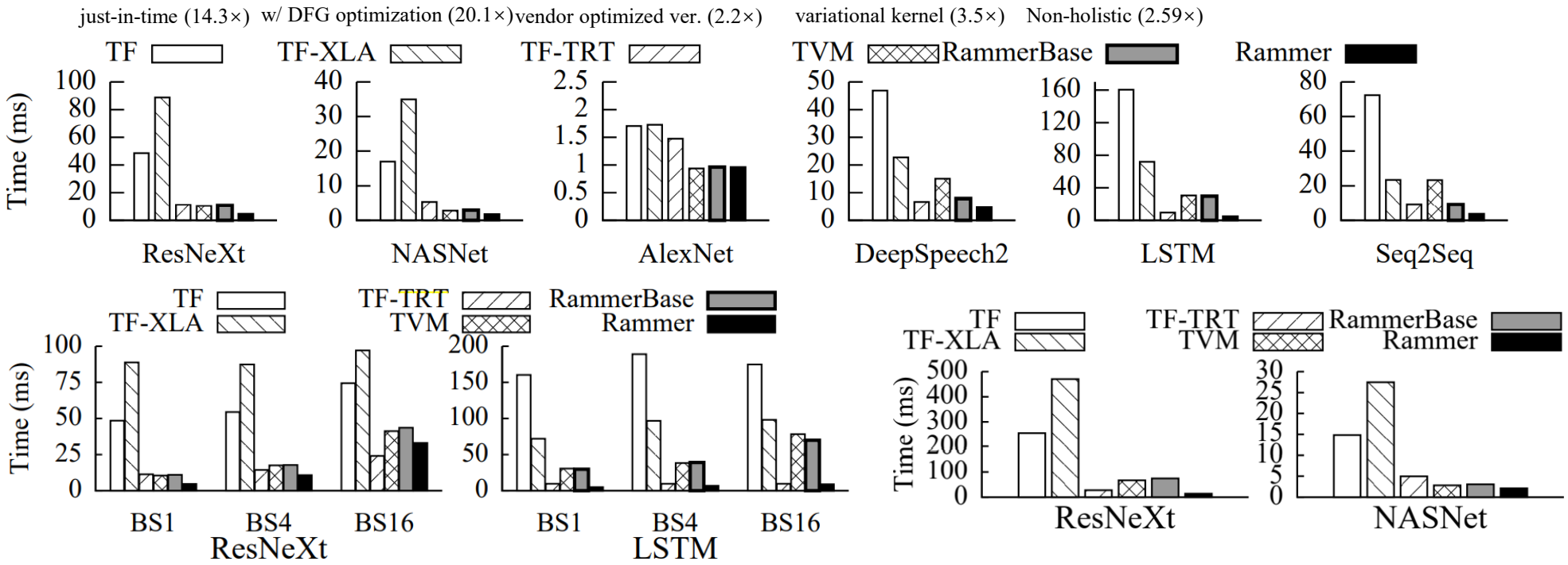
```
Data: G: DFG of rOperator, D: vDevice
Result: Plans: rPrograms
Function Schedule(G, D):
    P_curr = {};
    for W = Wavefront(G) do
        P_1 = ScheduleWave(W, P_curr, D);
        P_2 = ScheduleWave(W, {}, D);
        if time(P_1) ≤ time(P_curr) + time(P_2) then
            P_curr = P_1;
        else
            Plans.push_back(P_curr);
            P_curr = P_2;
    return Plans;
Function ScheduleWave(W, P, D):
    SelectRKernels(W, P);
    for op ∈ W do
        for r ∈ op.rTasks do
            vEU = SelectvEU(op, P, D);
            P.Wait(r, Predecessor(op).rTasks);
            P.Append(r, vEU);
    return P;
```

Corresponds to operator scheduler, implemented with BFS

Compile-time profiler

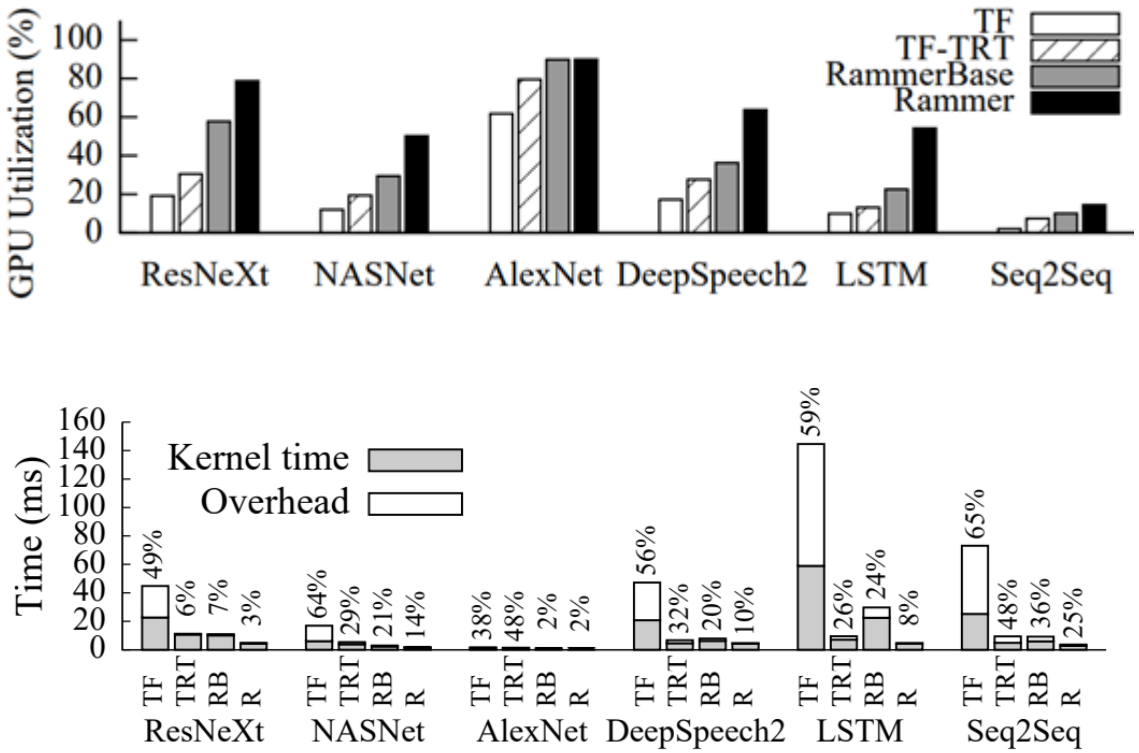
if most efficient implementations cannot saturate vDevice **then**
    Use most efficient implementations
else
    Try less efficient implementations for the most efficient operators
    Profile and accept if yield better running time

Experiments and Results

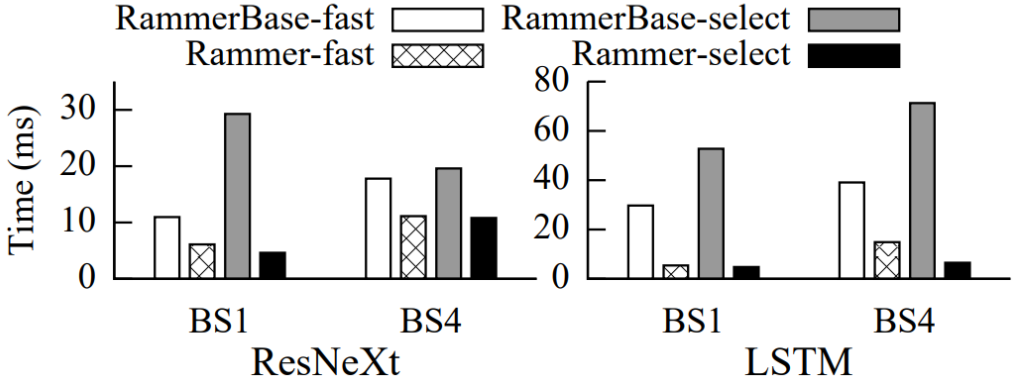


▲End2End results (overall inference time)

Experiments and Results



▲GPU utilization results and CPU runtime ratio results



▲Ablation study on *SelectRKernel*

Discussion

- Large data: Better performance boost when batch/input cannot saturate device.
- Dynamic graph: Since the schedule is determined at compile time, the model is required to be static for now.

Q&A

A Tensor Compiler for Unified Machine Learning Prediction Serving

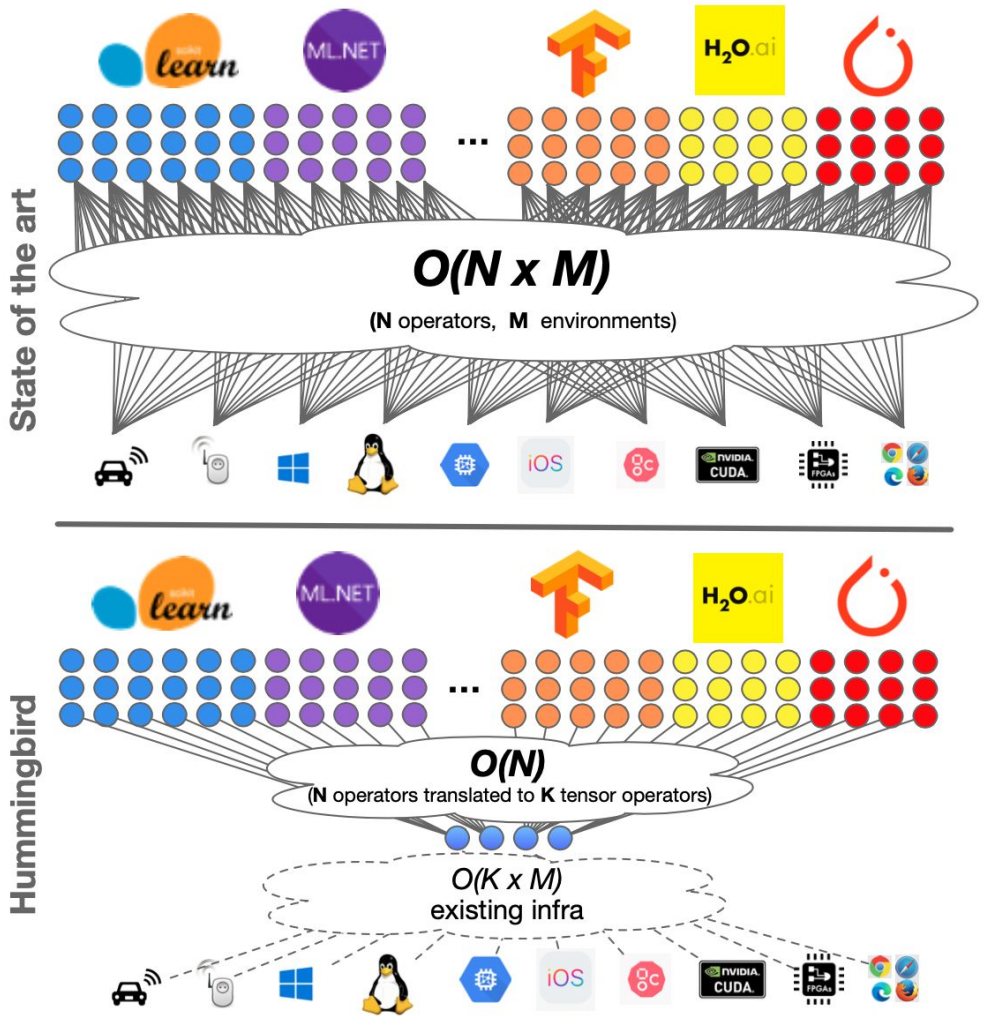
Supun Nakandala, Karla Saur, Gyeong-In Yu, Konstantinos Karanasos, Carlo Curino, Markus Weimer, Matteo Interlandi

14th USENIX Symposium on Operating Systems Design and Implementation

Motivation (1)

Traditional ML: Miss of abstraction leads to an O(N*M) explosion

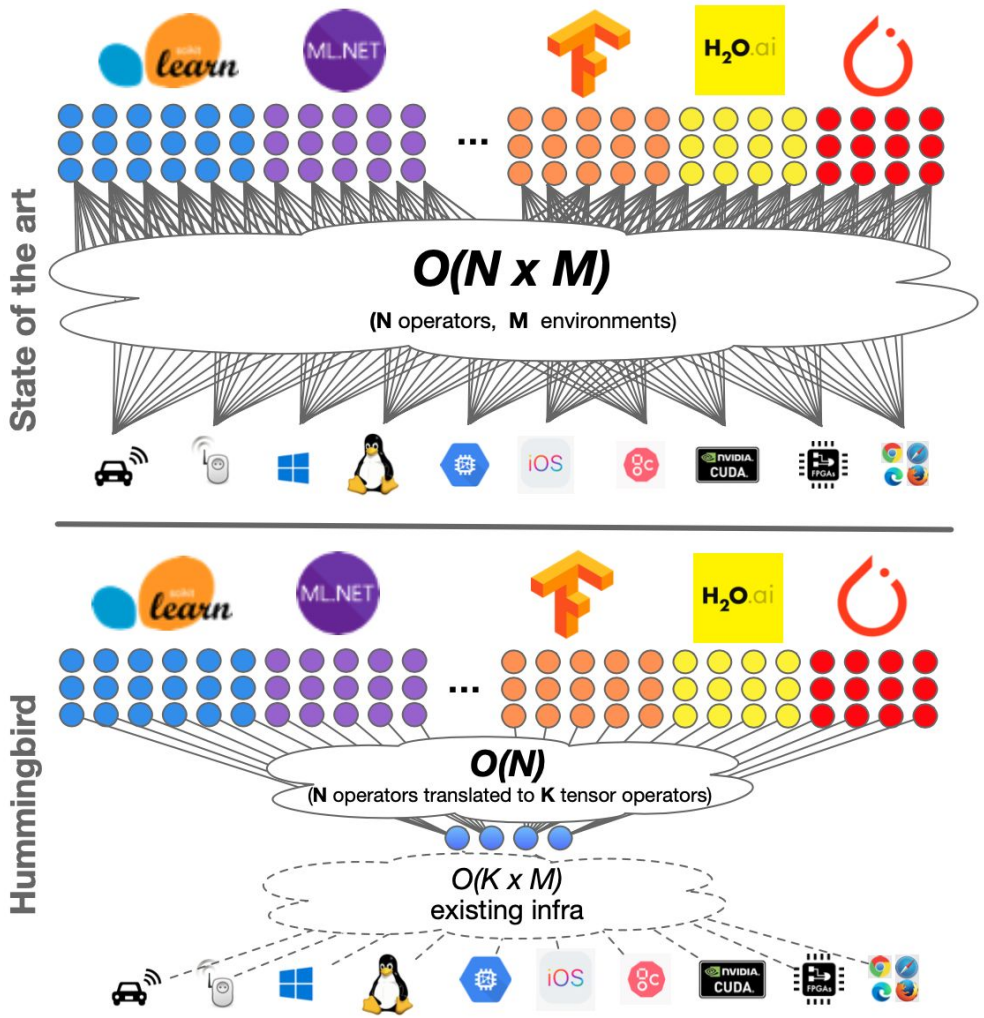
=> Hummingbird (HB) translates N operators into K core operators



Motivation (2)

Deep Neural Network (DNN): tensor transformation provides an algebraic abstraction

=> HB reduces traditional ML operators to tensor computations



Background

Predictive pipeline: the *iterative* process of designing and training traditional ML models

- a Directed Acyclic Graph (DAG) of typically tens of ***operators***

2 categories of operators:

- ***featurizers*** (e.g. string tokenizer, data normalization)
- ***models*** (e.g. linear models, decision tree ensembles)

Runtimes for DNN Inference: execute by implementing *a small set* of highly optimized operators on *multiple hardwares*

- e.g. ONNX Runtime (ORT) and TVM

How does HB work?

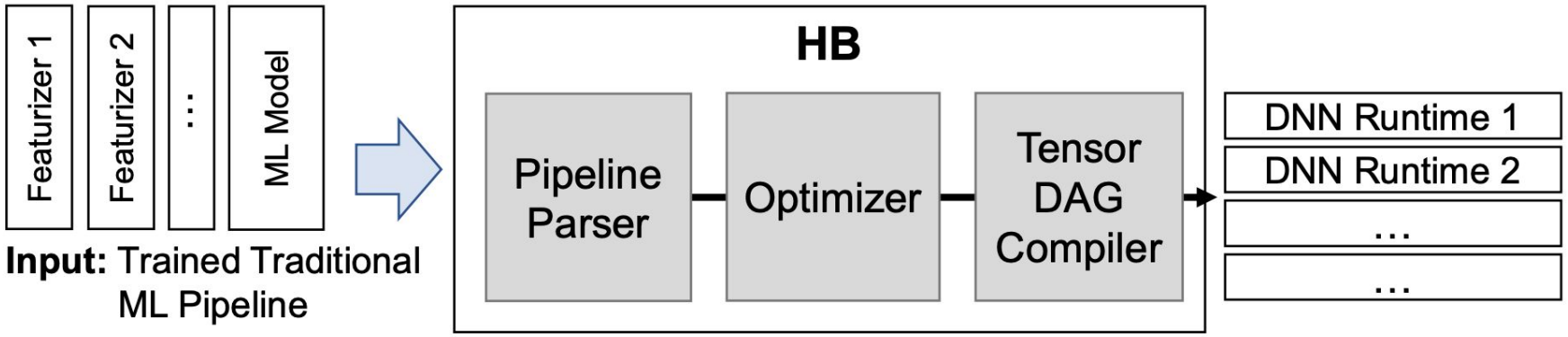
High-level idea:

introduces redundancies (both memory and *computation*) but utilize the efficient tensor operators

3 kinds of optimizations:

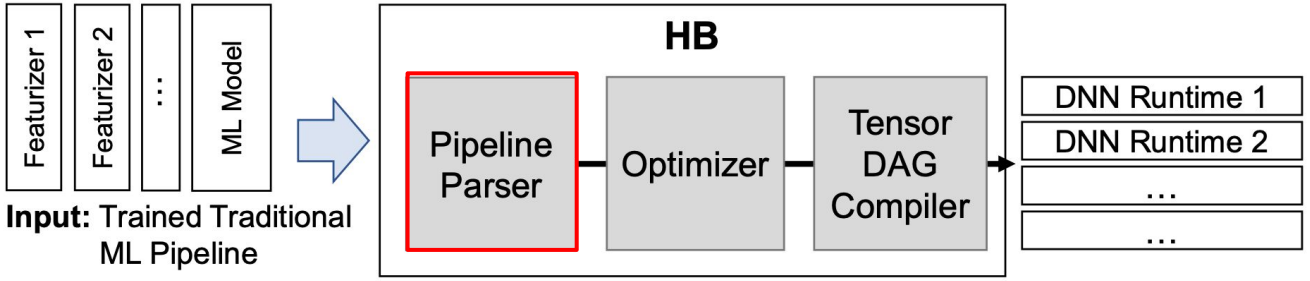
1. heuristics on compiler strategies selection (OPT1)
2. runtime-independent optimizations (OPT2)
3. runtime-specific optimizations (OPT3)

How does HB work?



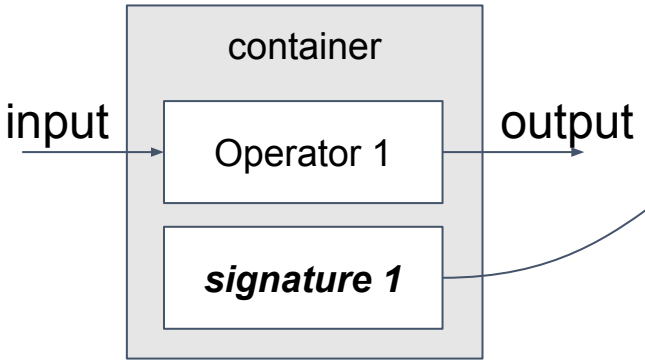
- **Pipeline parser**: parse operators into a DAG of containers
- **Optimizer**: (1) select compiler strategy; (2) apply runtime-independent optimizations **=> OPT1 and OPT2**
- **Tensor DAG Compiler**: convert to PyTorch *neural network module*, and export to target runtime format **=> OPT3**

Pipeline Parser



- parse operators into a DAG of ***containers***
- over 40 scikit-learn operators are supported in HB

For each operator:

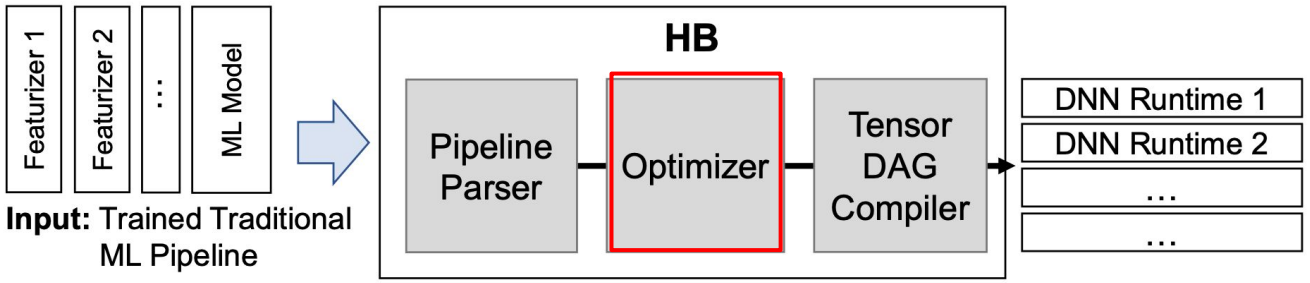


Build on start time:

extractor hash table	
signature 1	extractor 1
signature 2	extractor 2
...	...

extractor:
extract the parameters of each operator (e.g. thresholds of a decision tree).

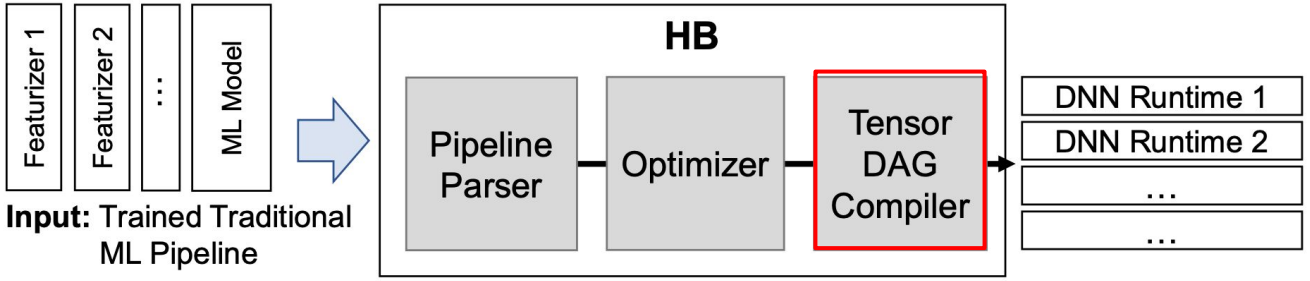
Optimizer



consist of 2 passes (traverse the DAG):

1. (prepare for the next step):
   a. extract parameters and store in container
   b. select the compiler strategy
2. apply runtime-independent optimizations
   a. **feature selection push-down**: similar to projection push-down in SQL
   b. **feature selection injection**: inject feature selection if not exist
      i. linear models: prune the zero weights
      ii. tree models: update the indices of the decision variables

Compiler



convert to PyTorch *neural network module*, and export to target runtime format (include runtime-specific optimizations)

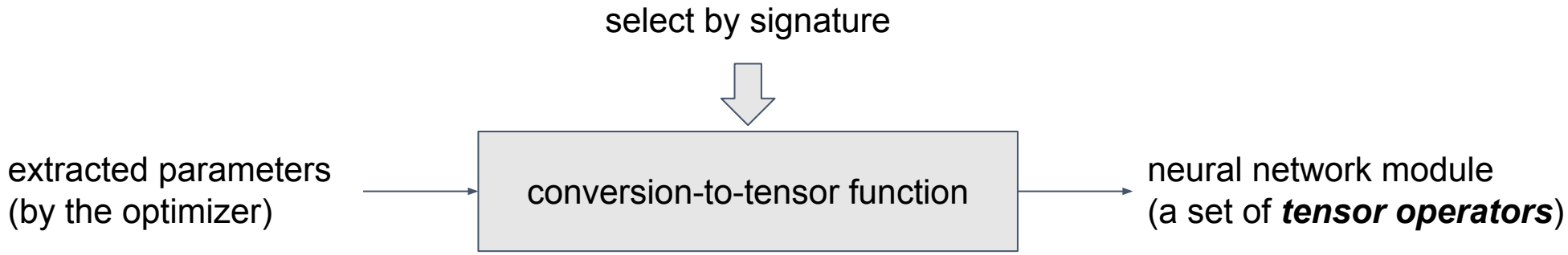


Table 2: PyTorch tensor operators used by the Tensor DAG Compiler.

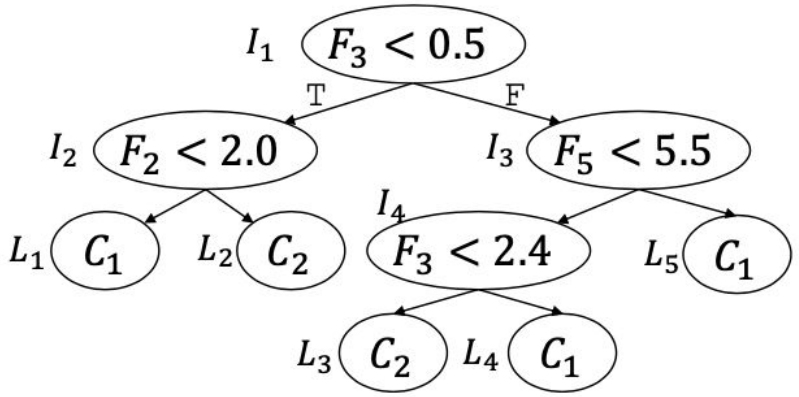
matmul, add, mul, div, lt, le, eq, gt, ge, &, |, ≪, ≫, bitwise_xor, gather, index_select, cat, reshape, cast, abs, pow, exp, arxmax, max, sum, relu, tanh, sigmoid, logsumexp, isnan, where

Compiler Example

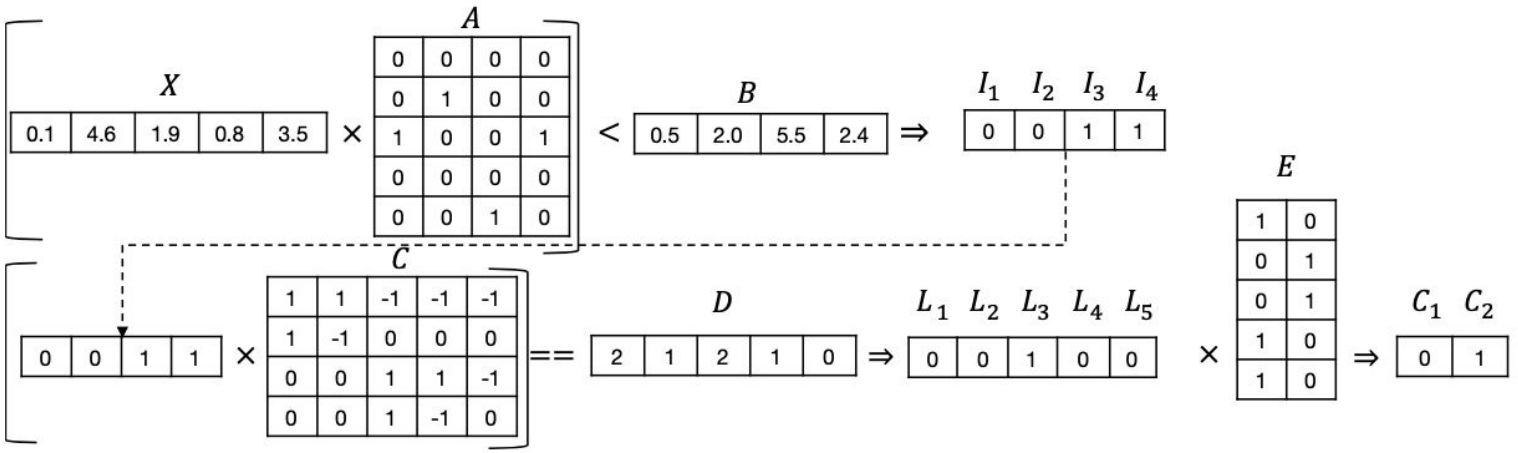
Strategies to compile tree-based model:

1. GEneric Matrix Multiplication (GEMM)
2. Tree Traversal (TT)
3. Perfect Tree Traversal (PTT)

GEneric Matrix Multiplication (GEMM)



What is the worst-case space/time complexity?



GEneric Matrix Multiplication (GEMM)

batch processing for trees of different sizes:

- pick the maximum size as the tensor dimensions
- pad the smaller tensor with zeros

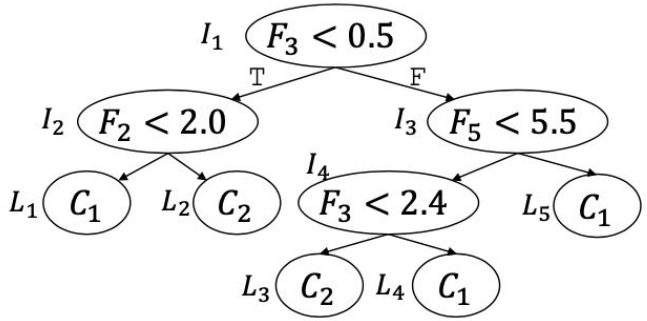
Input : $X \in \mathbb{R}^{n \times |F|}$, Input records
Output : $R \in \{0,1\}^{n \times |C|}$, Predicted class labels

```
/* Evaluate all internal nodes
```
$T \leftarrow \texttt{GEMM}(\mathbf{X}, \mathbf{A})$
$T \leftarrow T < B$

```
/* Find the leaf node which gets selected
```
$T \leftarrow \texttt{GEMM}(\mathbf{T}, \mathbf{C})$
$T \leftarrow T == D$

```
/* Map selected leaf node to class label
```
$R \leftarrow \texttt{GEMM}(\mathbf{T}, \mathbf{E})$

Tree Traversal (TT)



N_L:	2	4	6	4	5	8	7	8	9
N_R:	3	5	7	4	5	9	7	8	9
N_F:	3	2	5	1	1	3	1	1	1
N_T:	0.5	2.0	5.5	0	0	2.4	0	0	0
N_C:	0	0							
	0	0							
	0	0							
	1	0							
	0	1							
	0	0							
	1	0							
	0	1							
	1	0							

Input : $X \in \mathbb{R}^{n \times |F|}$, Input records
Output : $R \in \{0,1\}^{n \times |C|}$, Predicted class labels

```
/* Initialize all records to point to k, with k the index
   of Root node.                                          */
T_I ← {k}^n                                   // T_I ∈ Z^n
for i ← 1 to TREE_DEPTH do
    /* Find the index of the feature evaluated by the
       current node. Then find its value.                 */
    T_F ← Gather(N_F, T_I)                    // T_F ∈ Z^n
    T_V ← Gather(X, T_f)                      // T_V ∈ R^n
    /* Find the threshold, left child and right child     */
    T_T ← Gather(N_T, T_I)                    // T_T ∈ R^n
    T_L ← Gather(N_L, T_I)                    // T_L ∈ Z^n
    T_R ← Gather(N_R, T_I)                    // T_R ∈ Z^n
    /* Perform logical evaluation. If true pick from T_L;
       else from T_R.                                     */
    T_I ← Where(T_V < T_T, T_L, T_R)          // I ∈ Z^n
end
/* Find label for each leaf node                          */
R ← Gather(N_C, T_I)                          // R ∈ Z^n
```

Perfect Tree Traversal (PTT)

Assume a perfect binary tree

=> Remove N_L and N_R

=> reduce 2 Gather() per iteration

Input : $X \in \mathbb{R}^{n \times |F|}$, Input records
Output : $R \in \{0,1\}^{n \times |C|}$, Predicted class labels

```
/* Initialize all records to point to the root node.      */
```
$T_I \leftarrow \{1\}^n$ // $T_I \in \mathbb{Z}^n$

for $i \leftarrow 1$ **to** TREE_DEPTH **do**

```
    /* Find the index of the feature evaluated by the
       current node. Then find its value.                 */
```
    $T_F \leftarrow$ Gather(N_F, T_I) // $T_F \in \mathbb{Z}^n$
    $T_V \leftarrow$ Gather(X, T_f) // $T_V \in \mathbb{R}^n$

```
    /* Find the threshold                                 */
```
    $T_T \leftarrow$ Gather(N_T, T_I) // $T_T \in \mathbb{R}^n$

```
    /* Perform logical evaluation. If true pick left child;
       else right child.                                  */
```
    $T_I \leftarrow 2 \times T_I +$ Where$(T_V < T_T, 0, 1)$ // $I \in \mathbb{Z}^n$

end

```
/* Find label for each leaf node                          */
```
$R \leftarrow$ Gather(N'_C, T_I) // $R \in \mathbb{Z}^n$

Analysis of the Strategies

Strategy	Memory	Runtime
GEMM	$O(\|F\|\|N\| + \|N\|^2 + \|C\|\|N\|)$	$O(\|F\|\|N\| + \|N\|^2 + \|C\|\|N\|)$
TT	$O(\|N\|)$	$O(\|N\|)$
PTT	$O(2^{\|N\|})$	$O(\|N\|)$

=> Heuristics-based strategy selection

Other Techniques in the Compiler

1. Exploit Automatic Broadcasting
   a. broadcast: make two tensors shape compatible (reshape)
2. Minimize Operator Invocations
3. Avoid Generating Large Intermediate Results
4. Fixed Length Restriction on String Features

Performance

Task 1: Micro-benchmarks

- Tree ensembles
- Various other operators

Task 2: Optimizer

Task 3: End-to-end pipelines

Performance :Tree Ensembles (1)

3 algorithms, 6 datasets, CPU & GPU, HB on 3 different runtimes

Baseline:

- CPU: Sklearn, ONNX-ML
- GPU: RAPIDS FIL

conduct 8 experiments (batch inference, request/response, scaling batch size, etc.)

Performance: Tree Ensembles (2)

batch inference:

- CPU: HB-TVM outperforms on 15/18
- GPU: HB-TVM outperforms on 14/18

request/response (batch size = 1): HB-TVM outperforms on 11/15, 3x speedup

output validation:

- HB has no mismatch on 9/18 (12/18 for ONNX-ML)
- For Epsilon dataset: mismatch 0.1% records (11.5% for ONNX-ML)

Performance: Other Operators

test on 13 operators supported by both ONNX-ML and HB (Logistic Regression, Normalizer, etc.)

batch inference:

- CPU: HB-TVM outperforms on 8/13
- GPU: HB-TorchScript outperforms on 11/13

request/response:

- ONNX-ML outperform on 9/13
- all frameworks are within a factor of 2

Performance: Optimizer

Between GEMM, TT & PTT:

- GEMM outperforms for small batch sizes
- TT/PTT are better over large batch sizes, PTT is usually better
- PTT fails for very deep trees

Feature selection push-down

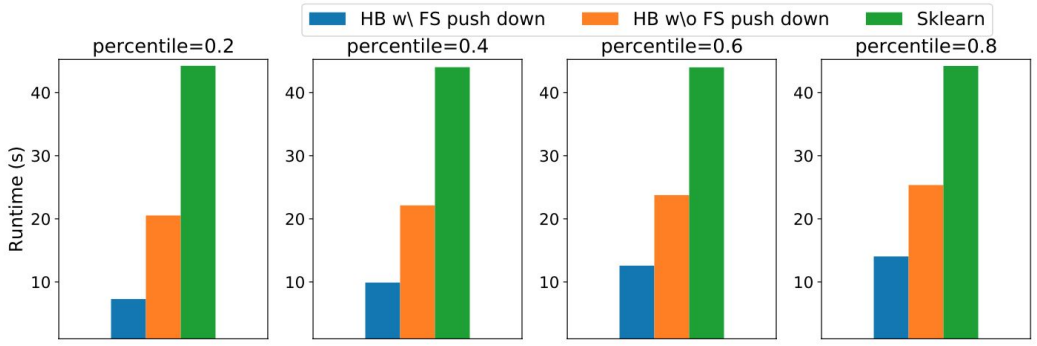


Figure 9: Feature selection push down.

Feature selection injection

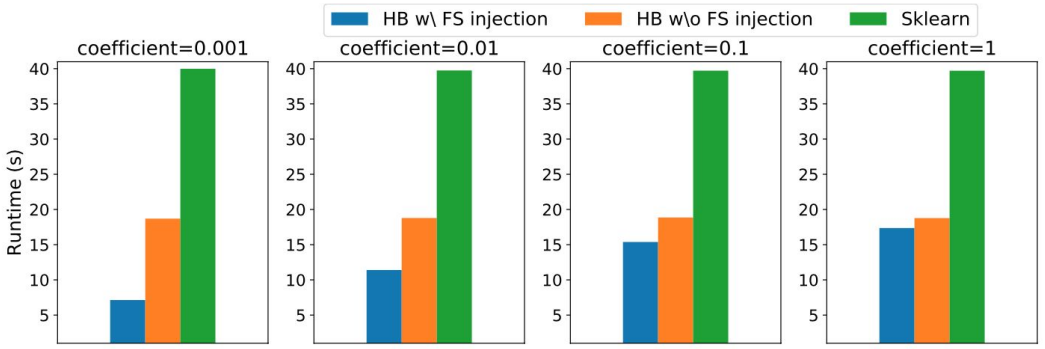


Figure 10: Feature selection injection.

Performance: End-to-end pipeline

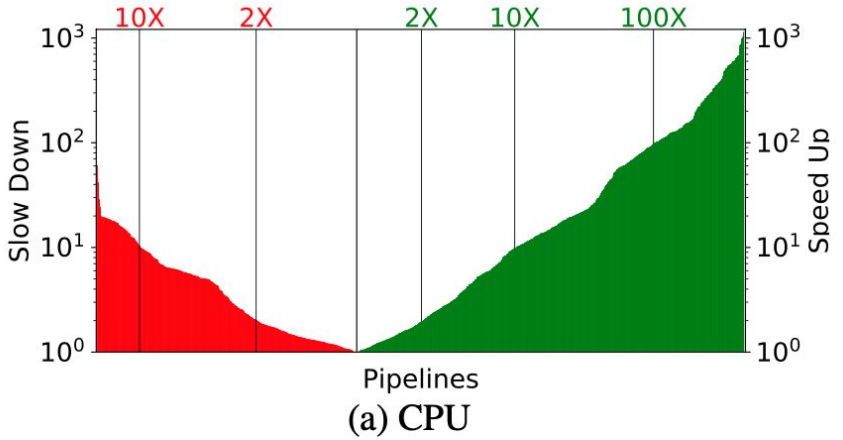
2317 pipelines (avg 3.3 operators)

CPU: 60% pipelines see speedup

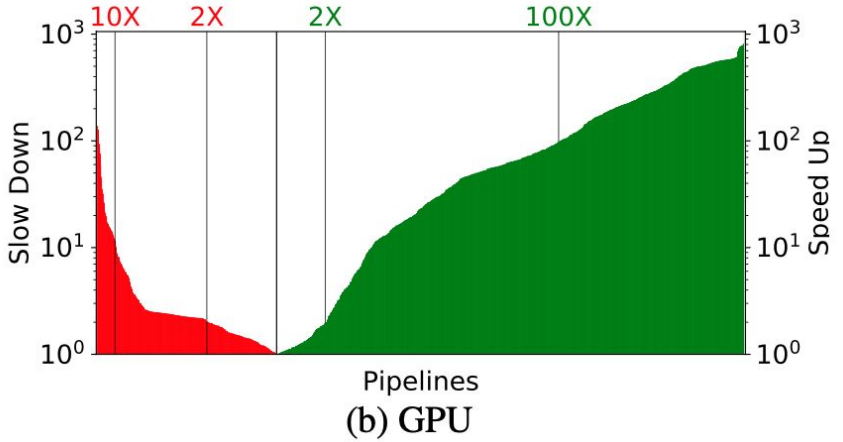
GPU: 73% pipelines see speedup

reasons for slowdown:

1. dataset is too small
2. sparse operators
3. pipeline does not require much computation



(a) CPU



(b) GPU

How it contributes?

Use two-level optimization approach

1. runtime-independent optimizer (OPT2)
2. strategy selection (OPT1) and other physical rewrites (supported by DNN runtimes, OPT3)

Provide 3 tree inference strategies

Q&A