## BOLT: BRIDGING THE GAP BETWEEN AUTO-TUNERS AND HARDWARE-NATIVE PERFORMANCE Xing et. al. (2021)

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### Auto-tuners vs hardware-native libraries

### **Auto-tuners**

- Structural tensor program optimization
- the search space

• Generate training sets of sample programs - use performance to navigate

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Workload(M,N,K)

### **Auto-tuners**

- Strenghts:
  - Platform generality
- Weaknesses:
  - Performance (vs. vendor libraries)
  - Long search



- Modularized and composable
  - Templates initiated for different hardware and workloads

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  - Performance superior to hardware-opaque auto-tuning

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  - Performance superior to hardware-opaque auto-tuning
- Weaknesses:
  - Parameters too low-level
  - Usually only for a part of a model





- - Deeper operator fusion (graph level)



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  - Automated template code generation operator level



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  - Automated template code generation operator level
  - (System-friendly models model level)

Pre-requisite: **Epilogue Fusion** (provided by CUTLASS)

- General Matrix Multiply (GEMM)/Convolution Kernels
- Epilogue Kernels (element-wise operators, data type conversion, data type conversion, broadcast vector over columns, partial reduction over columns)

## **Persistent Kernel**

- Fuses GEMMs & Convolutions
- Eliminates activation storing & loading in global memory
- Eliminates kernel initializations

## **Persistent Kernel**

- Requires:
  - GEMM: dimensional compatibility
  - Convolution: filter restrictions

## **Persistent Kernel**

- Bolt:
  - Identifies opportunities to use persistent kernels
  - Generates new code using templates (using CUDA code)

### Non-fused:



### Epilogue fusion:

GEMM1	Bias	ReLU	
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### Persistent kernel fusion:

GEMM1 Bi	ias ReLU	GEMM2	Bias	ReLU
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**BYOC** (bring your own codegen)

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 Offload parts of code from the compiler (TVM) to templated libraries (CUTLASS)

## "Light-weight performance profiler"

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- Searches for best template parameters
  - Target hardware-informed
  - Templated libraries whiteboxes
    - Further optimization possibilities

# System-Friendly Models

• Epilogue fusion: explore activation functions

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- Persistent kernel: model deepening with 1x1 convolutions

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- Epilogue fusion: explore activation functions
- Persistent kernel: model deepening with 1x1 convolutions
- Efficient tensor shapes: padding of unaligned tensors





Normalized speed

# Evaluation

Workload (M,N,K)

## Comparison: GEMMs



## Comparison: Convolutions

Normalized speed

# Evaluation

Workload ((H, W), (IC, OC), strides)



## Comparison: end-to-end inference speed

# Evaluation

Models

# Evaluation



## Comparison: end-to-end tuning speed

Models

- Integrated into TVM (CUTLASS)
  - <u>https://github.com/apache/tvm/pull/9261</u>
- Actively used by Bytedance



# Critique



End-to-end testing only on convolution based models

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- Limited fusion exploration

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## • Paper not too accessible (eg. many unexplained abbreviations and names)