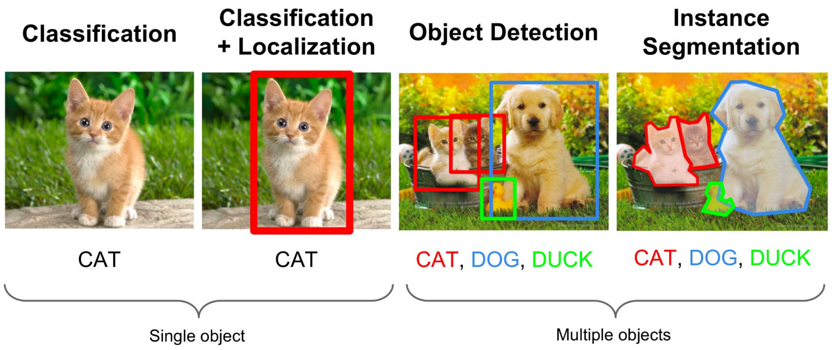
OpenAI

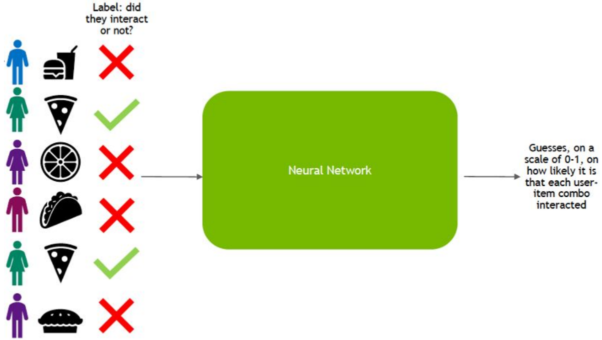
Towards Agile Development of Efficient Deep Learning Operators

OpenAI Research Acceleration Team
Presenter: Keren Zhou

Deep Neural Networks (DNNs)



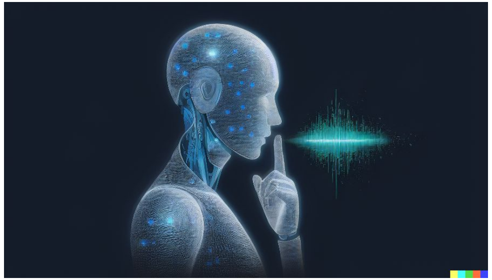
Computer Vision



Recommendation Systems

ChatGPT

Natural Language Processing



Speech Recognition

Image sources

https://chaosmail.github.io/deeplearning/2016/10/22/intro-to-deep-learning-for-computer-vision/
https://medium.com/@ageitgey/machine-learning-is-fun-part-6-how-to-do-speech-recognition-with-deep-learning-28293c162f7a
https://towardsdatascience.com/language-translation-with-rnns-d84d43b40571
https://developer.nvidia.com/blog/how-to-build-a-winning-recommendation-system-part-2-deep-learning-for-recommender-systems/

Transform DNNs to Low Level Code

```
a = torch.randn(64, 32)
b = torch.randn(32, 64)
c = torch.randn(64, 64)
d = torch.mm(a, b)
e = c + d
```

Model	Graph	Kernel	Device
• PyTorch • TensorFlow • JAX	• XLA/HLO • TVM/Relay • PyTorch/fx	• CUDA • HIP • OpenCL	• GPU • CPU • FPGA

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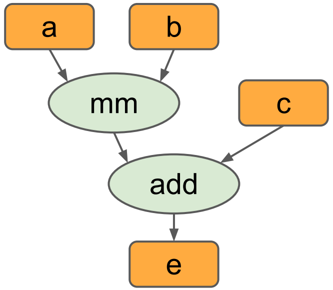

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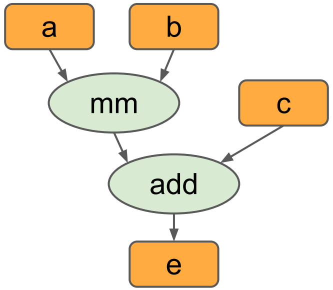


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__global__
void mm(float *a, float *b,
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    float *a_tile;
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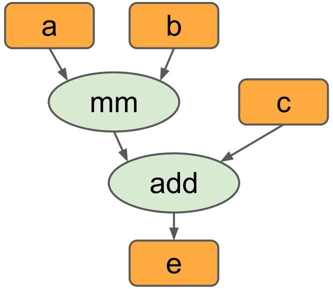


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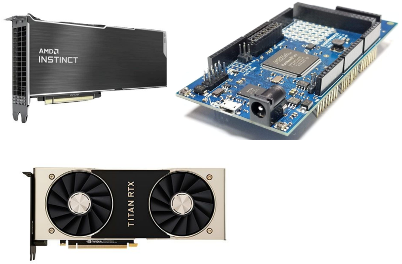

Model

- PyTorch
- TensorFlow
- JAX

Graph

- XLA/HLO
- TVM/Relay
- TorchDynamo

Kernel

- CUDA
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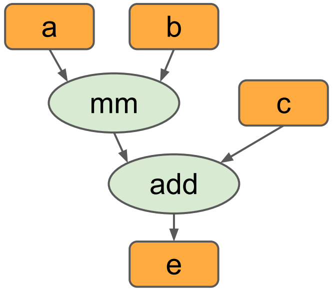


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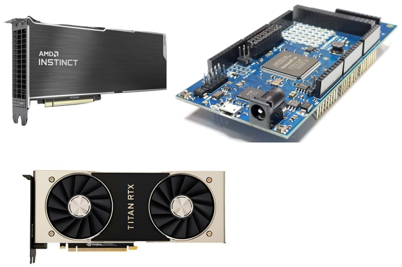

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A Large Number of Tensor Operators

- Linear
  - Fused
    - Attention
    - Bilinear
  - Sparse
    - SDDMM
    - SPMM
- Convolution
  - Depthwise
  - Dilated
  - Transposed
- Pooling
  - Max/Min/Avg
  - Adaptive
- Normalization
  - Batch
  - Layer
- Loss
  - NLL
  - BCE
- Embedding
- Recurrent
  - LSTM
  - GRU

Thousands of Operators in PyTorch and TensorFlow

Various Data Types

- ➔ Common tensor data types
  - Float64
  - Float32
  - Float32
  - Float16
  - BFloat16
  - Int64
  - Int32
  - Int16
  - Int8
  - Bool

For performance critical kernels:
#Implementations ≈
#Data types ✕ #Kernels

Handwritten Code

- **Low** flexibility
  - Fine-tune for every shape/data type/algorithm
  - Employ assembly instructions
  - …
- **High** performance
  - Apply sophisticated instruction/operator scheduling
  - Simplify code
  - …

Handwritten Code is a Pain

- For the company
  - Hard to hire new Machine Learning Engineers
  - Difficult to maintain libraries
- For the researchers
  - A black box
    - They want to understand how kernels work
    - They want to fast validate new ideas at scale

Python-like Code

- ➔ **High** flexibility
  - Build upon existing operators
  - No need to recompile
  - …
- ➔ **Low** performance
  - Not fine-tuned for specific shapes
  - Intermediate memory movement
  - …

Can we design a language to achieve both
high performance and flexibility?

Triton

A Programming Model for the Next Generation Deep Learning Systems

Programming Models for DNNs

Model	• PyTorch • TensorFlow • JAX
Graph	• XLA/HLO • TVM/Relay • TorchDynamo
Kernel	• CUDA • HIP • OpenCL

Programming Models for DNNs

Model	• PyTorch • TensorFlow • JAX
Graph	• XLA/HLO • TVM/Relay • TorchDynamo
Kernel	• CUDA • HIP • OpenCL • Triton

Inefficiencies of PyTorch V1

- A neural network with individual kernels
  - Can be slow
  - Can run out-of-memory
- A neural network with graph compiler (TorchScript)
  - Don’t support custom data-structures
    - lists/trees of tensors
    - block-sparse tensors
  - Don’t support custom precision format
  - Automatic kernel fusion is limited

Solution: Employ Triton -> PyTorch V2 (TorchDynamo)

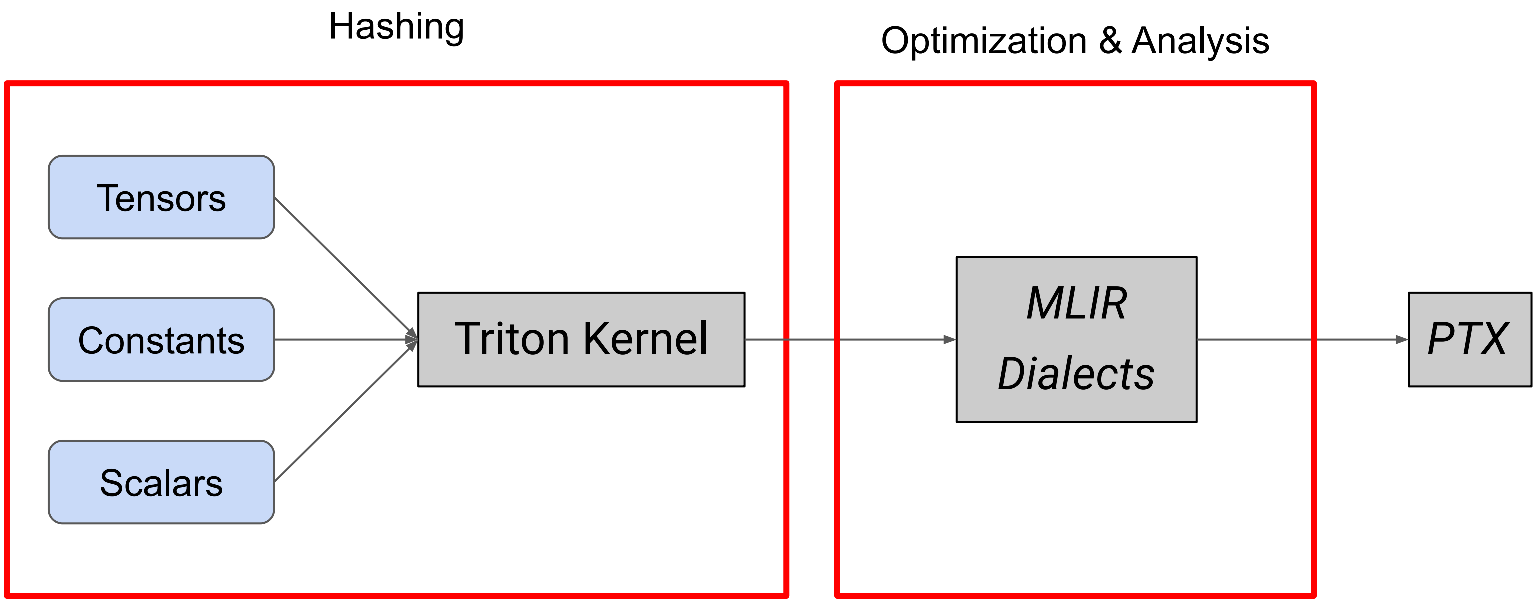
Triton is Designed to Achieve Both High Flexibility and Performance

- Flexibility
  - A small core set of operations (~40 interface functions and ~20 core functions)
  - Can be composed into almost all existing PyTorch operators (TorchInductor)
  - SPMD but not SIMT
- Performance
  - JIT generated kernels
  - Handwritten PTX code
  - Many passes to combine, simplify, and schedule operations

Triton is a Python-Like Language

- ➔ PyTorch compatible
  - ◆ Inputs can be PyTorch tensors or custom data-structures (e.g., tensors of pointers)
- ➔ Python syntax
  - ◆ All standard python control flow structure (for/if/while/return) are supported
  - ◆ Python code is lowered to Triton IR

Triton JIT-Compilation Workflow



Optimization Passes

- ➔ Triton specific optimizations
    - ◆ Pipeline
    - ◆ Prefetch
    - ◆ Matmul accelerate
    - ◆ Coalesce
    - ◆ Reorder
- ➔ MLIR optimizations
    - ◆ CSE, DCE, Inlining, …

R\C	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	T0:{a0,a1}		T1:{a0,a1}		T2:{a0,a1}		T3:{a0,a1}		T0:{a4,a5}		T1:{a4,a5}		T2:{a4,a5}		T3:{a4,a5}	
1	T4:{a0,a1}		T5:{a0,a1}		T6:{a0,a1}		T7:{a0,a1}		T4:{a4,a5}		T5:{a4,a5}		T6:{a4,a5}		T7:{a4,a5}	
2																
..																
7	T28:{a0,a1}		T29:{a0,a1}		T30:{a0,a1}		T31:{a0,a1}		T28:{a4,a5}		T29:{a4,a5}		T30:{a4,a5}		T31:{a4,a5}	
8	T0:{a2,a3}		T1:{a2,a3}		T2:{a2,a3}		T3:{a2,a3}		T0:{a6,a7}		T1:{a6,a7}		T2:{a6,a7}		T3:{a6,a7}	
9	T4:{a2,a3}		T5:{a2,a3}		T6:{a2,a3}		T7:{a2,a3}		T4:{a6,a7}		T5:{a6,a7}		T6:{a6,a7}		T7:{a6,a7}	
10																
..																
15	T28:{a2,a3}		T29:{a2,a3}		T30:{a2,a3}		T31:{a2,a3}		T28:{a6,a7}		T29:{a6,a7}		T30:{a6,a7}		T31:{a6,a7}	

%laneid:{fragments}

Analysis Passes

- ➔ Shared memory
  - ◆ Alias
  - ◆ Liveness
  - ◆ Barrier
- ➔ Pointer alignment
- ➔ Call graph
  - ◆ “noinline” functions

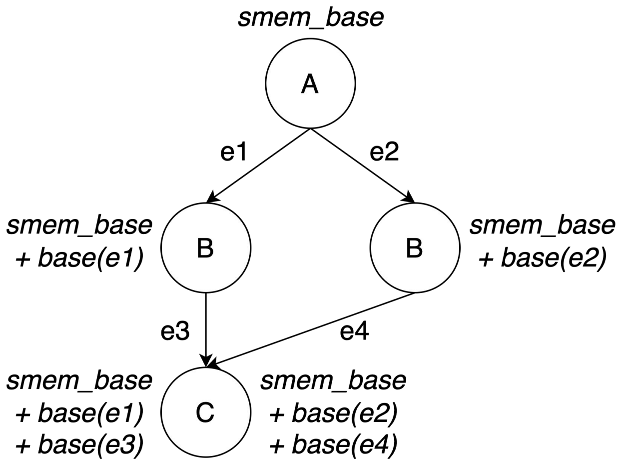
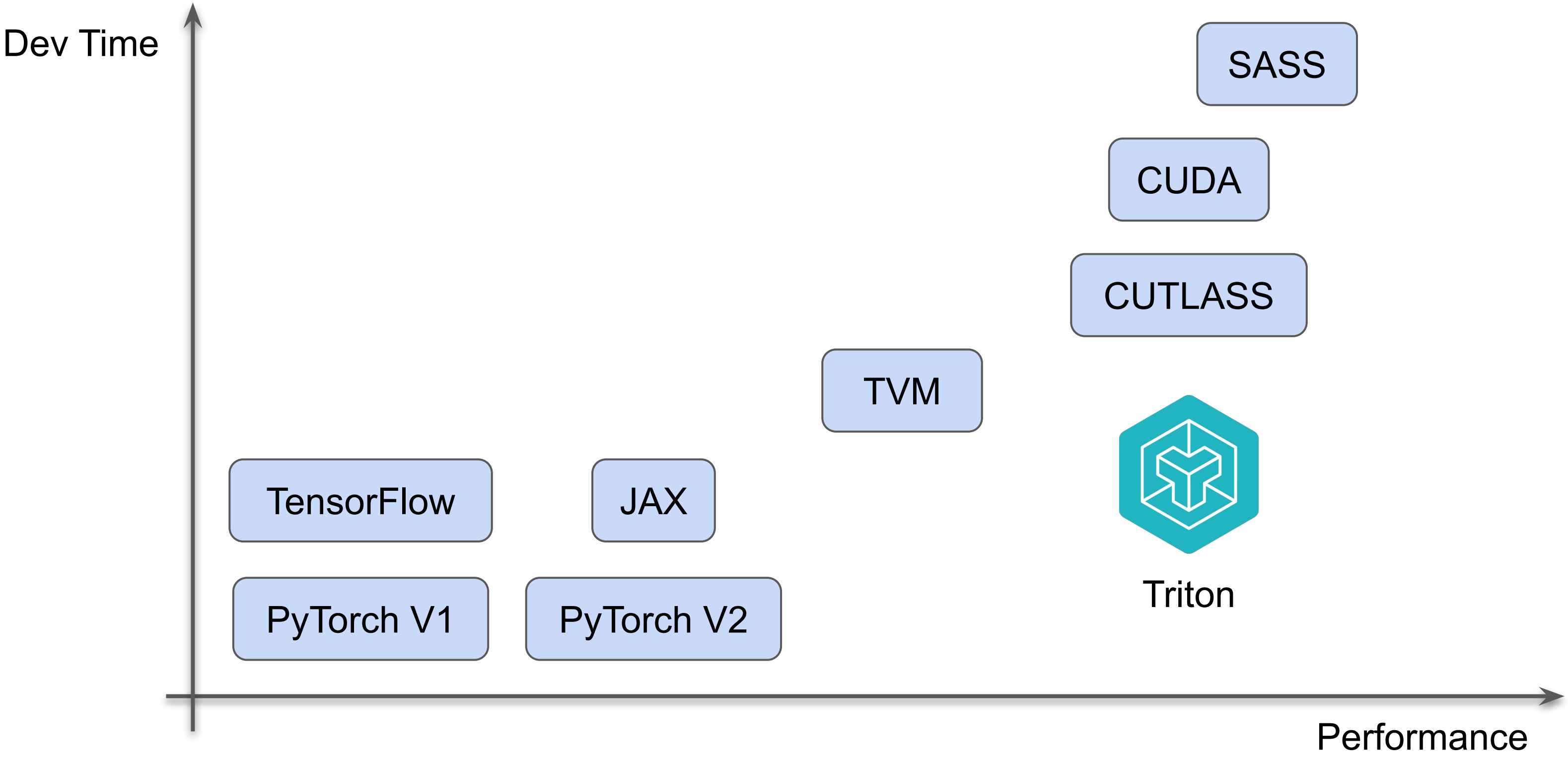


Figure 2

Dev Time *VS* Performance



Write GPU Kernels Using Triton

Terminologies

- ➔ Parallelism
  - ◆ Grid
    - One for each kernel (Pre-Hopper)
  - ◆ Block/Warp/Thread
- ➔ Memory
  - ◆ Global
    - Visible to all threads
  - ◆ Shared
    - Private to each block
  - ◆ Local
    - Private to each thread

CUDA *vs* Triton

	CUDA	**Triton**
Memory	Global/Shared/Local	Automatic
Parallelism	Threads/Blocks/Warps	Mostly Blocks
Tensor Core	Manual	Automatic
Vectorization	.8/.16/.32/.64/.128	Automatic
Async SIMT	Support	Limited
Device Function	Support	Support

Using Triton, you only need to know that a program is divided into multiple blocks

Vector Addition (Single Block)

- ➔ Z[:] = X[:] + Y[:]
  - ◆ Without boundary check

```python
import triton.language as tl
import triton
```

```python
N = 1024
x = torch.randn(N, device='cuda')
y = torch.randn(N, device='cuda')
z = torch.randn(N, device='cuda')
```

Vector Addition (Boundary Check)

- ➔ Z[:] = X[:] + Y[:]
  - ◆ With boundary check

```python
@triton.jit
def _add(z_ptr, x_ptr, y_ptr, N):
    # same as torch.arange
    offsets = tl.arange(0, 1024)

    # create 1024 pointers to X, Y, Z
    x_ptrs = x_ptr + offsets
    y_ptrs = y_ptr + offsets
    z_ptrs = z_ptr + offsets
    # load 1024 elements of X, Y, Z


    # do computations
    z = x + y
    # write-back 1024 elements of X, Y, Z


N = 192311
x = torch.randn(N, device='cuda')
y = torch.randn(N, device='cuda')
z = torch.randn(N, device='cuda')
grid = (triton.cdiv(N, 1024), )
_add[grid](z, x, y, N)
```

Vector Addition (Custom Tile Size)

- ➔ Z[:] = X[:] + Y[:]
  - Each block computes TILE elements
- ➔ @triton.autotune
  - Select the best config based on the execution time
  - We don't want to build complex autotune policies into Triton

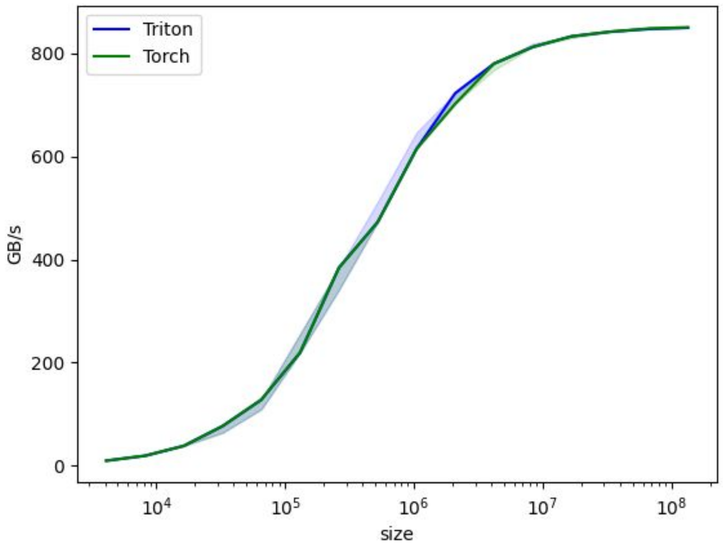
```python
@triton.jit
def _add(z_ptr, x_ptr, y_ptr, N):
    # same as torch.arange
    offsets = tl.arange(0, TILE)
    offsets += tl.program_id(0)*TILE
    # create 128/256 pointers to X, Y, Z
    x_ptrs = x_ptr + offsets
    y_ptrs = y_ptr + offsets
    z_ptrs = z_ptr + offsets
    # load 128/256 elements of X, Y, Z
    x = tl.load(x_ptrs, mask=offset<N)
    y = tl.load(y_ptrs, mask=offset<N)
    # do computations
    z = x + y
    # write-back 128/256 elements of X, Y, Z
    tl.store(z_ptrs, z, mask=offset<N)

N = 192311
x = torch.randn(N, device='cuda')
y = torch.randn(N, device='cuda')
z = torch.randn(N, device='cuda')
```

Performance of Triton Kernels

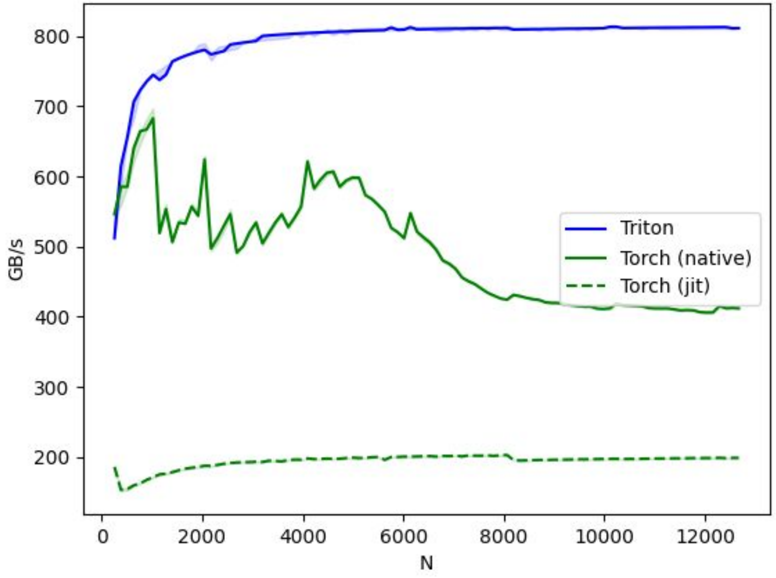
Element-wise Operators

- ➔ Triton and Torch both achieve peak bandwidth
- ➔ Researchers can write *fused element-wise operators* easily using Triton



Fused Softmax

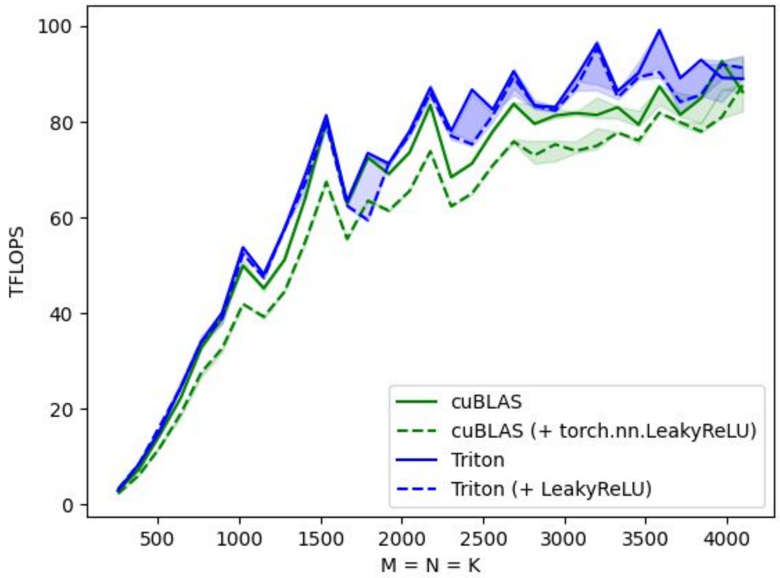
- ➔ Triton kernels can keep data on-chip throughout the entire softmax
- ➔ PyTorch JIT could in theory do that but in practice doesn't
- ➔ The native PyTorch op is designed to work for every input shape and is slower in cases where we care



Matrix Multiplication

➔ It takes <25 lines of code to write a Triton kernel on par with cuBLAS

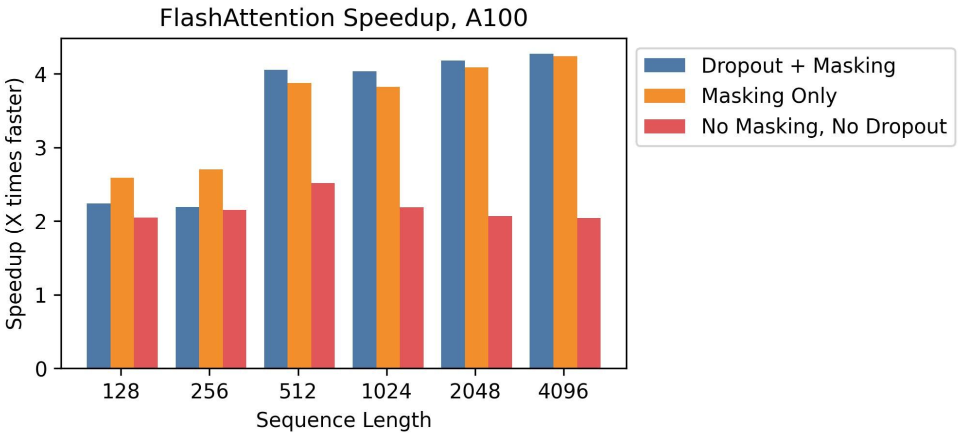
➔ Arbitrary ops can be “fused” before/after the GEMM while the data is still on-chip, leading to large speedups over PyTorch

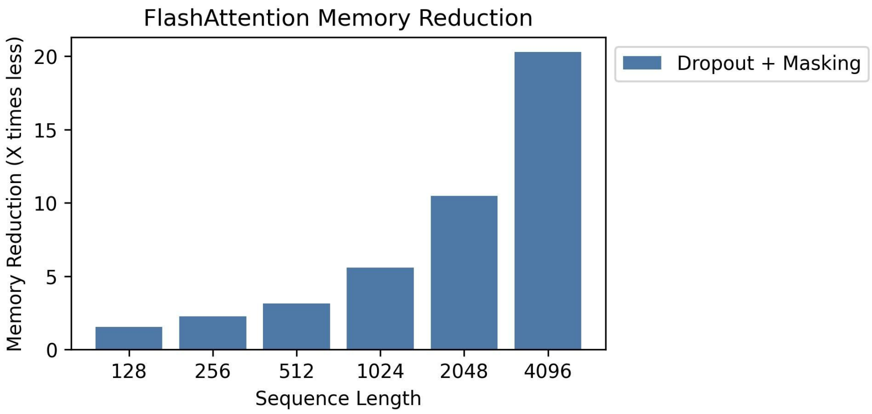


Fused Attention (Flash Attention)

➔ **From the author:** Triton is easier to understand and experiment with than CUDA

➔ Triton forward + backward is slightly slower than CUDA forward + backward



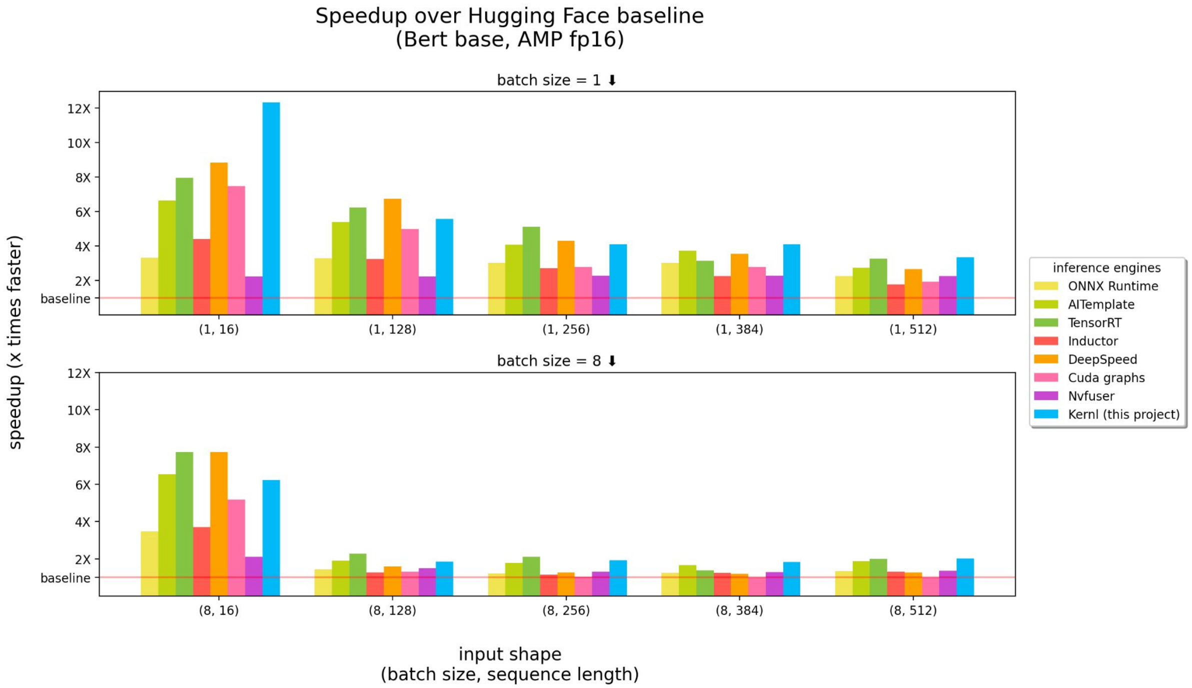


FlashAttention: Fast and Memory-Efficient Exact Attention with IO-Awareness
Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, Christopher Ré
Paper: https://arxiv.org/abs/2205.14135

Kernl

➔ Run PyTorch transformer models several times faster on GPU with a single line of code

➔ The first OSS inference engine written in Triton



https://github.com/ELS-RD/kernl/

Contributing to Triton

Goals

➔ Make Triton more robust

➔ Using existing infrastructure to avoid creating new wheels

➔ Support more backends

Ecosystem

deepspeed

tinygrad

kernl.ai

Runtime

Debugger

Profiler

PyTorch

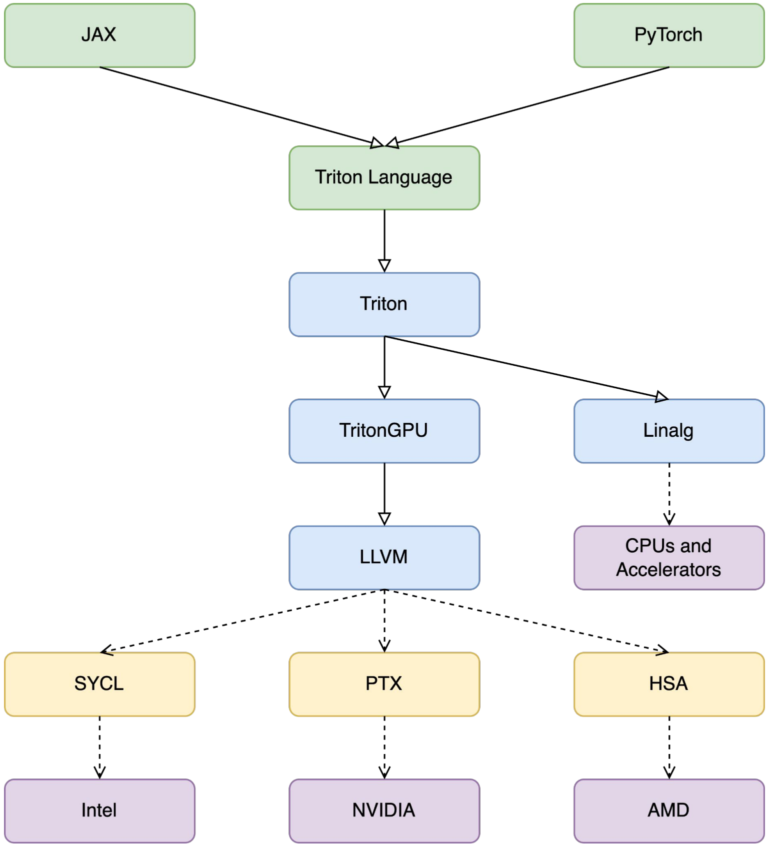
Language

OpenXLA

IREE

Backends

Backend Status



Collaborations @ Intel

➔ Started from this thread

- Thanks to Eikan Wang, Chengjun Lu, and etc.

[Triton-SPIRV] General idea and question on Triton #811

chengjunlu started this conversation in **Ideas**

chengjunlu on Oct 27, 2022

Hi **@ptillet** ,

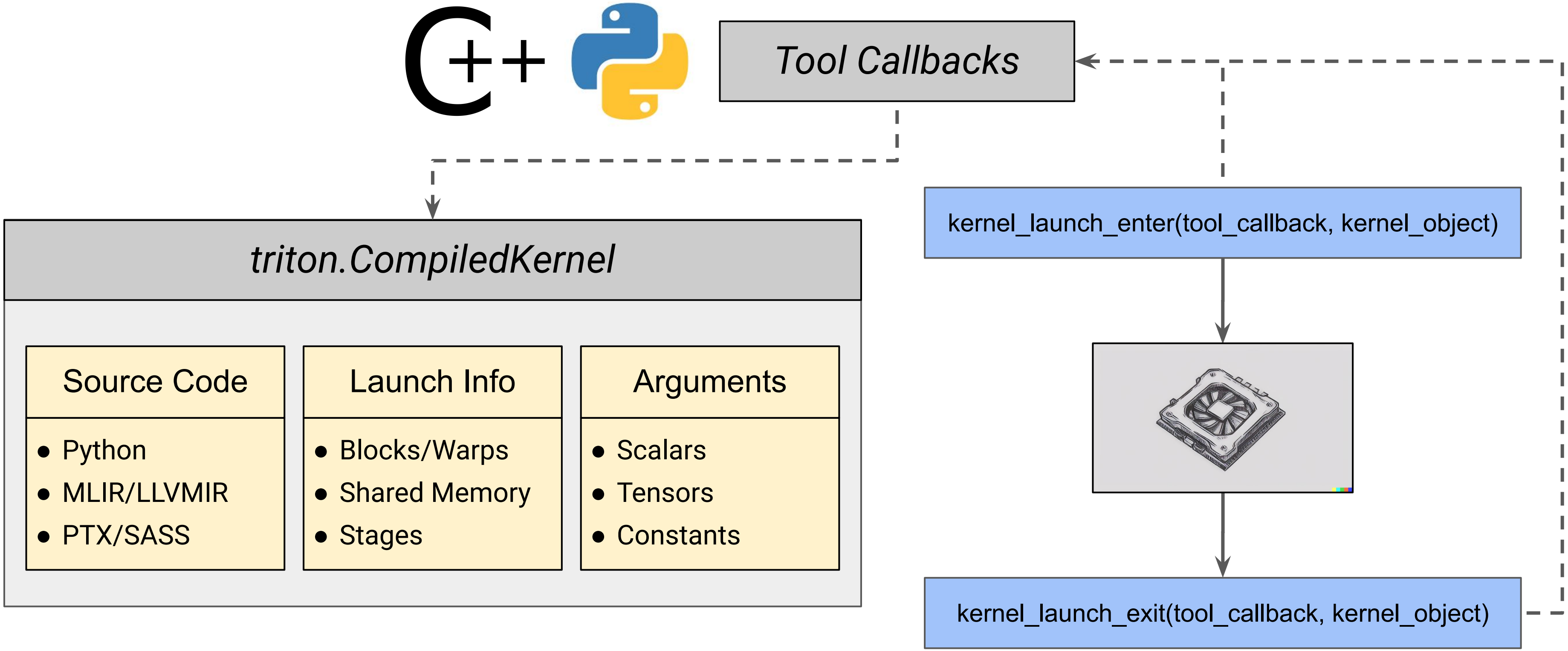
I am bringing up the Triton on Intel GPU.

The integration idea is naively thru:
TritonIR -> LLVM with SPIRV intrinsic -> SPV kernel -> SYCL runtime to run the kernel on Intel GPU platform.

Potential Tool Support for Triton

- ➔ Debugger
  - ◆ Detect memory leaks/data race/uninitialized values
    - On par with NVIDIA’s compute-sanitizer
- ➔ Profiler
  - ◆ Trace multiple processes with low overhead
    - On par with NVIDIA’s Nsight Systems
  - ◆ Measure accurate kernel times and instruction stall reasons
    - On par with NVIDIA’s Nsight Compute

Callback Design



Takeaways

- ➔ Triton is designed to achieve both high performance and flexibility
- ➔ Triton has been used widely in open source projects
- ➔ Triton supports multiple GPU backends already
    - ◆ NVIDIA GPUs provide the highest performance

Community Meetings

➔ We will be starting (tentatively monthly) 1-hour long virtual community meetings to give the opportunity to triton users and developers to ask questions, provide feedback, or present their work. The first inaugural meeting will happen on July 19th at 10am PST via Google Meet

- meet.google.com/jsw-bvej-ekz

Thank You

Visit openai.com for more information.

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