FLASHLIGHT: PyTorch Compiler Extensions to Accelerate Attention Variants

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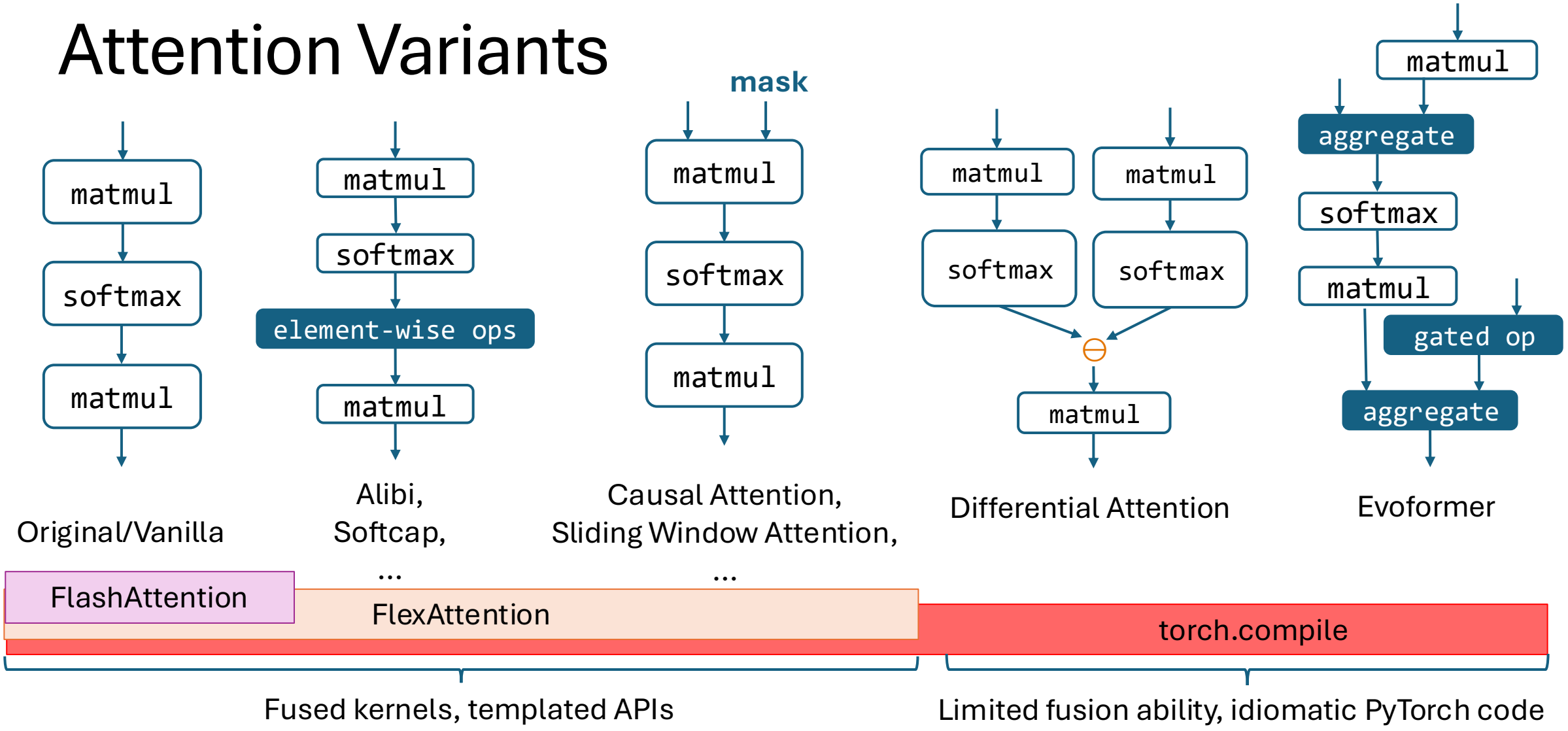
https://github.com/bozhiyou/flashlight

Attention Variants



FLASHLIGHT generates optimized, fused kernels from idiomatic PyTorch code

FLASHLIGHT in a Nutshell

General extensions to PyTorch compiler (torch.compile)

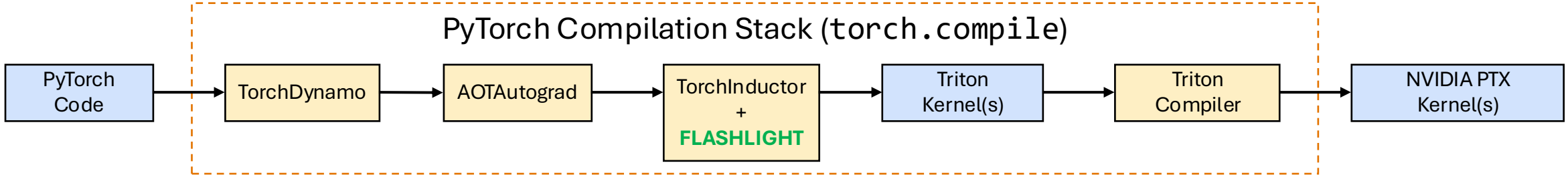
- Generates I/O-efficient Triton kernels from *idiomatic* PyTorch code
  - Even for variants not supported by FlexAttention or FlashAttention
- Moves the optimization burden from the *user* to the *compiler*

Superior performance

- Always faster than default PyTorch Compiler
- For FlexAttention-supported variants: similar performance
- Beyond FlexAttention: **5x** faster for Evoformer
  - Improves end-to-end inference latency for AlphaFold by 6 to 9%

FLASHLIGHT: An Augmented Torch

General extensions to TorchInductor, *not* a standalone compiler

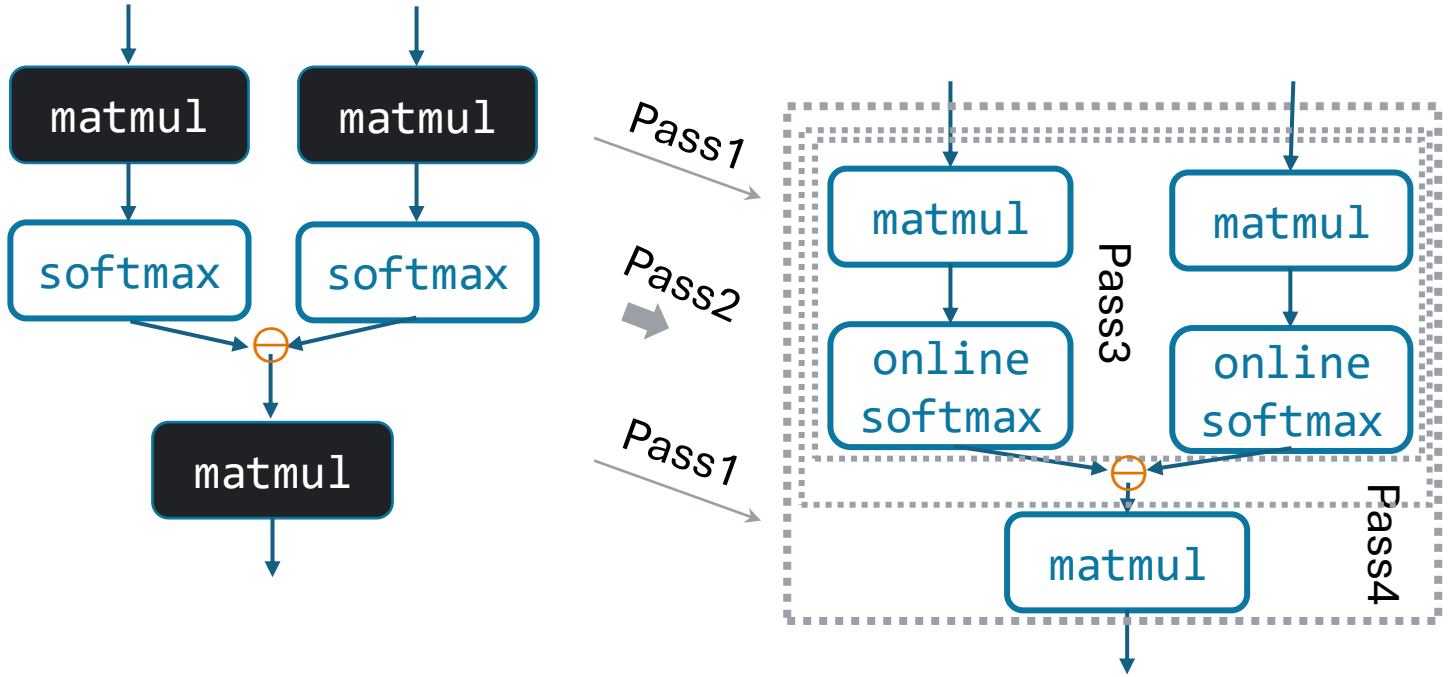


1. Unified Reduction IR

2. Algebraic Transformation

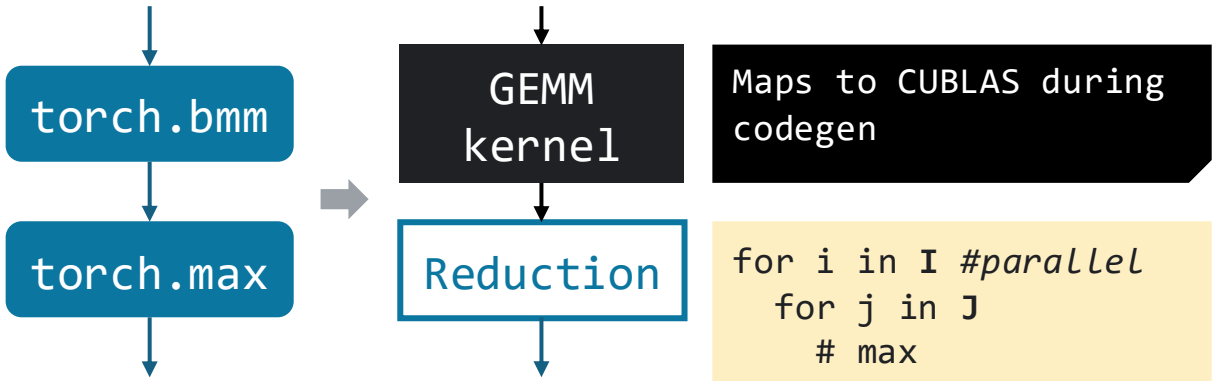
3. Dimension Demotion

4. Tiling-Aware Dimension Elimination



FLASHLIGHT (1/4): Unified Reduction IR

Before/Default

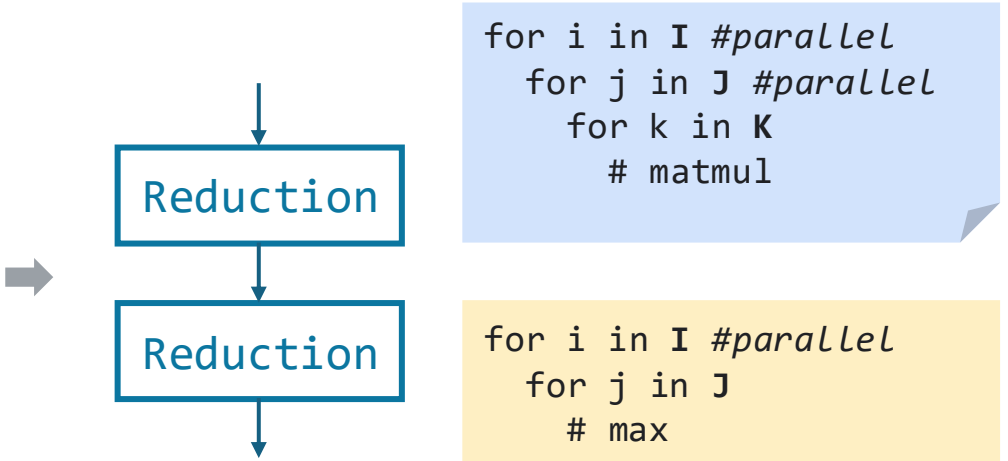


Compute Graph

Inductor IR

Optimized GEMM kernel but artificial fusion boundary

With FLASHLIGHT



Inductor IR

Enables fusing matmul with reductions (sacrifices CUBLAS performance for fusion opportunities)

FLASHLIGHT (2/4): Algebraic Transformation

Before/Default

$$\text{softmax}(x) = \frac{e^{x-\max x}}{\sum e^{x-\max x}}$$

```
m = -inf
for j in J
  m = max(m, x[p1])
```

```
s = 0
for j in J
  s = s + exp(x[p1] - m)
```

Second loop/pass depends on first => fusion boundary

With FLASHLIGHT

```
m = -inf
s = 0
for j in J
  m_ = max(m, x[p1])
  s = s * exp(m - m_)
  s = s + exp(x[p1] - m_)
  m = m_
```

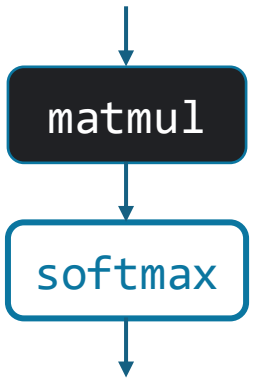
Homomorphism: $h(f(a,b)) = \mathrm{g}(h(a), h(b))$

$\exp(\text{sub}(a,b)) = \text{div}(\exp(a), \exp(b))$: $e^{a-b} = \frac{e^a}{e^b}$

Single loop/scan => enables fusion

FLASHLIGHT (3/4): Dimension Demotion

Any "parallel" dim can be treated as a "reduction" dim
=> demote fusable "parallel" dim to "reduction" dim
(sacrifices parallelism for I/O efficiency)



Pass 1

```
for i in I #parallel
  for j in J #parallel
    for k in K
      # matmul
```

Pass 2

```
for i in I #parallel
  for j in J #reduction
    # softmax
```

Pass 3

```
for i in I #parallel
  for j in J #reduction
    for k in K
      # matmul
```

```
for i in I #parallel
  for j in J #reduction
    # softmax
```

```
for i in I #parallel
  for j in J
    for k in K
      # matmul
    # softmax
```

Single fused kernel for:

$$A = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})$$

FLASHLIGHT (4/4): Tiling-Aware Dimension Elimination

When H (head dim) is small,
set tile_size_of_H = H so that |TH| = 1 to drop TH loop
(requires logical grid dimensions)

```
for i in I #parallel
  for j in J
    for k in K
      # matmul
    # softmax
```

```
for i in I #parallel
  for h in H
    for j in J
      # matmul
```

```
for ti in TI #parallel
  for tj in TJ
    for tk in TK
      # tile of matmul
    # tile of softmax
```

```
for ti in TI #parallel
  for th in TH
    for tj in TJ
      # tile of matmul
```

```
for ti in TI #parallel
  for tj in TJ
    for tk in TK
      # tile of matmul
    # tile of softmax
```

```
for ti in TI #parallel
  # |TH| = 1
  for tj in TJ
    # tile of matmul
```

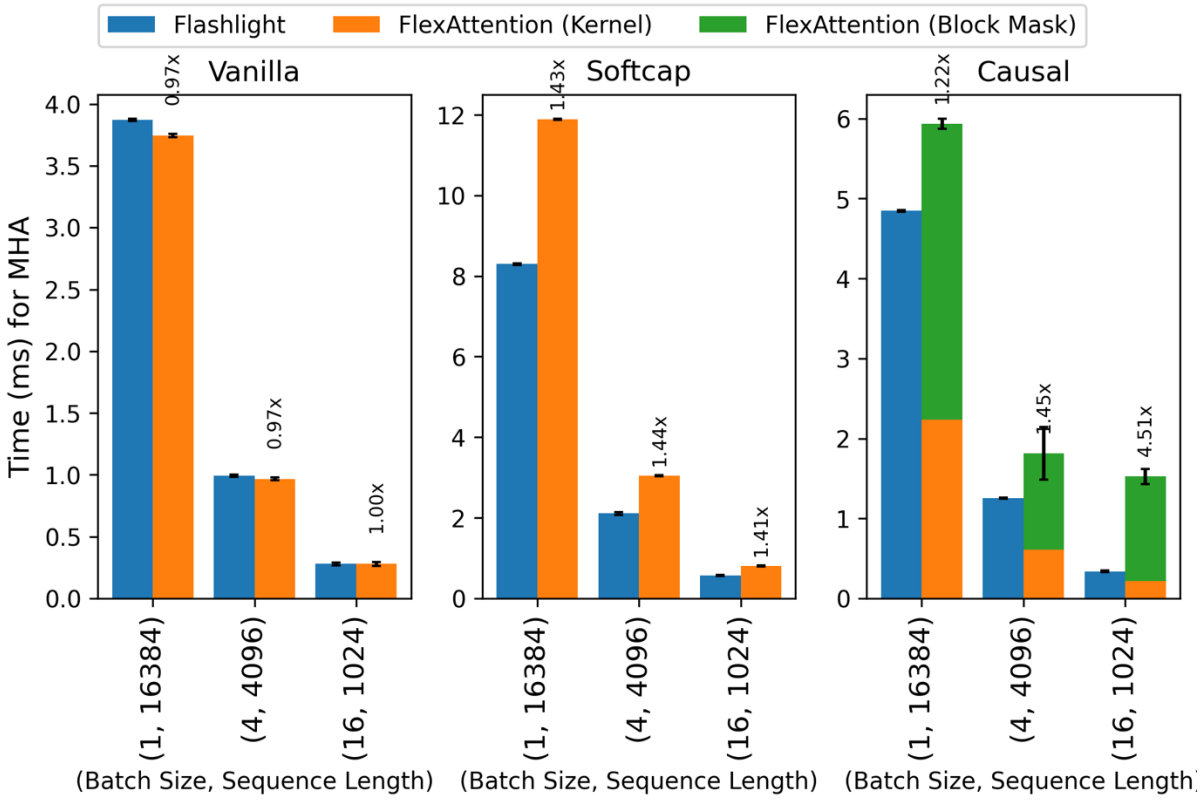
```
for ti in TI #parallel
  for tj in TJ
    for tk in TK
      # tile of matmul
    # tile of softmax
    # tile of matmul
```

Single fused kernel for:

$$A = \mathbf{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)\mathbf{V}$$

Evaluation: Flex-Supported Attention Variants on H100

How do FLASHLIGHT *generated* kernels compare to FlexAttention's *specialized* template?

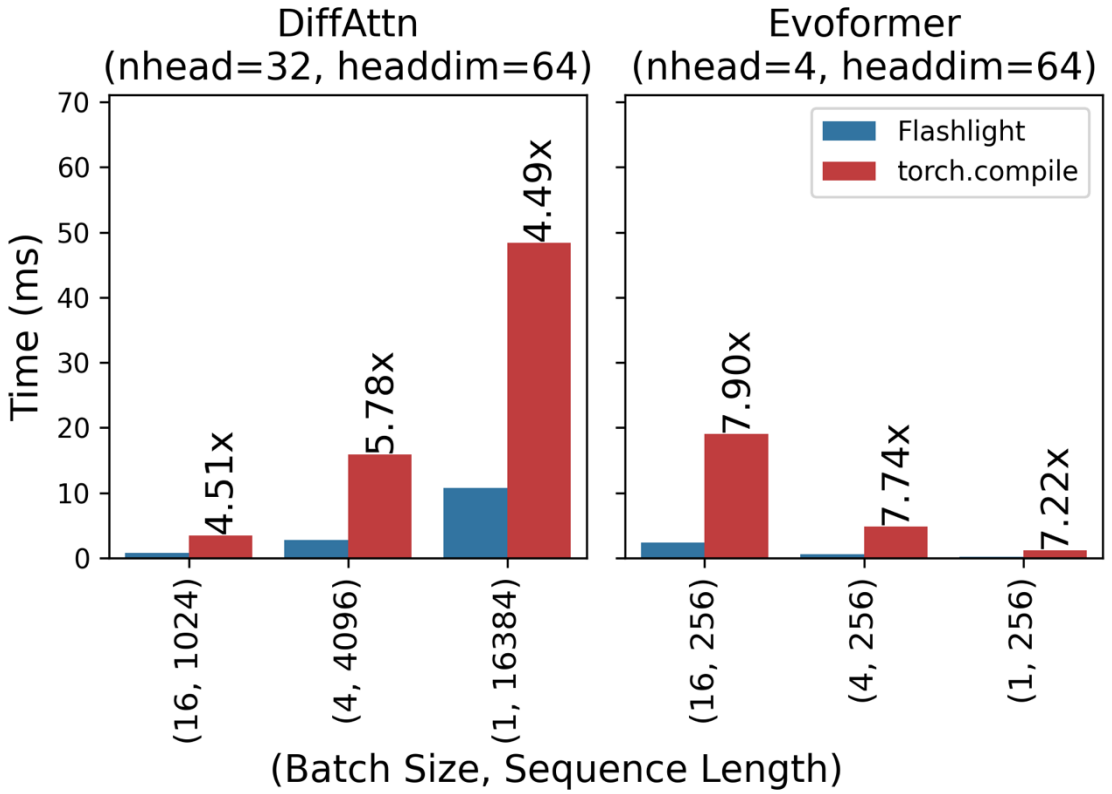


Refer to the paper for more results

FLASHLIGHT is competitive or faster than FlexAttention

Evaluation: Complex Attention Variants on H100

What about the complex attention variants that FlexAttention cannot handle?



Refer to the paper for more results

FLASHLIGHT is significantly faster than default torch.compile

FLASHLIGHT: Summary

General extensions to PyTorch compiler (torch.compile)

- Generates I/O-efficient Triton kernels from *idiomatic* PyTorch code
  - Even for variants not supported by FlexAttention or FlashAttention
- Moves the optimization burden from the *user* to the *compiler*

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