Building Compilers for Deep Learning

using PyTorch and LLVM MLIR

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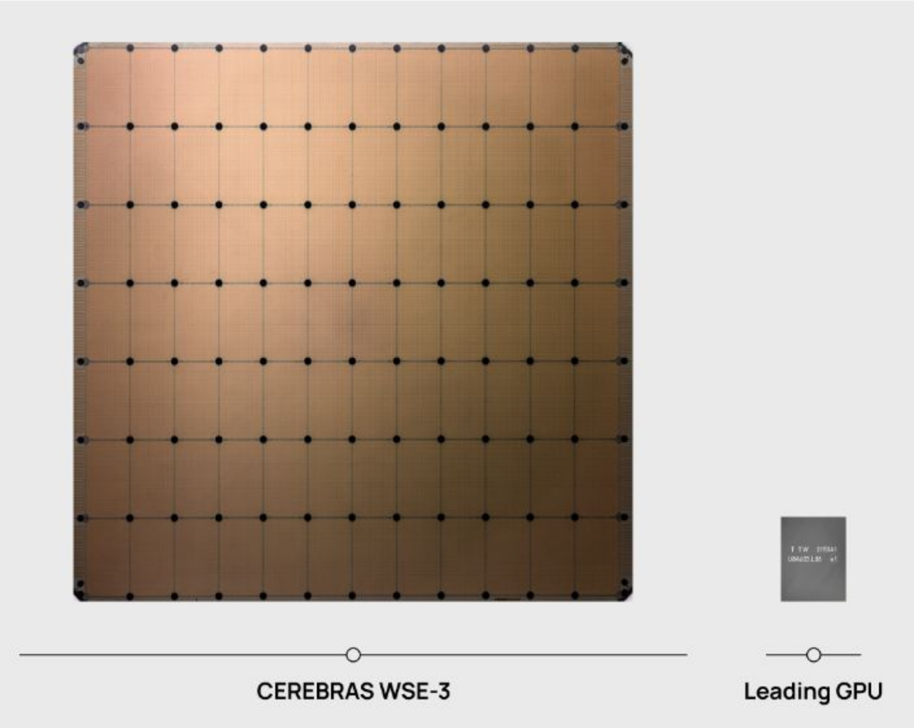
http://david.g3ns.de
Cerebras Systems Inc.

March, 2025

ICYMI: Cerebras Systems builds Wafer-Scale Engines!



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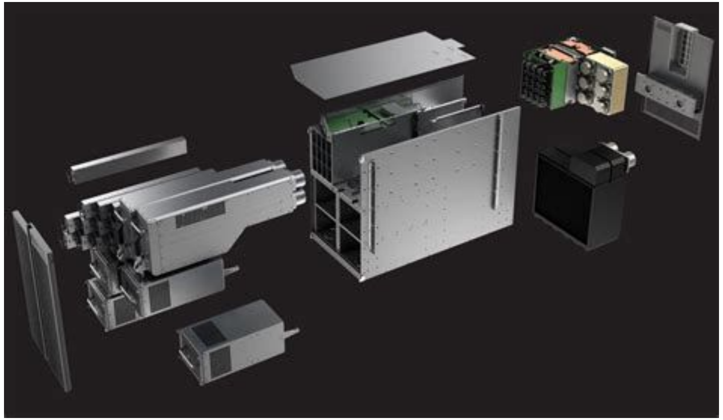
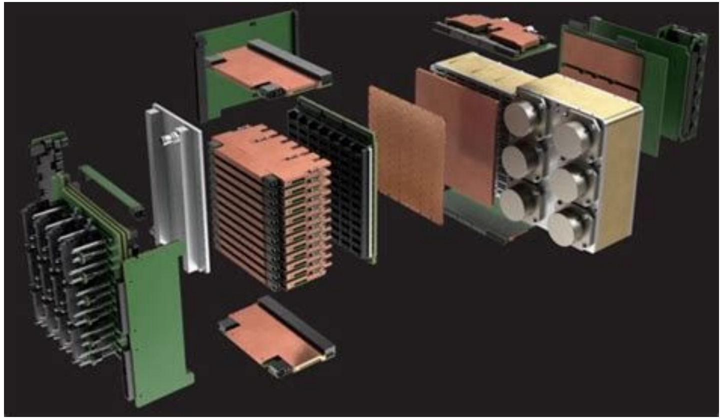
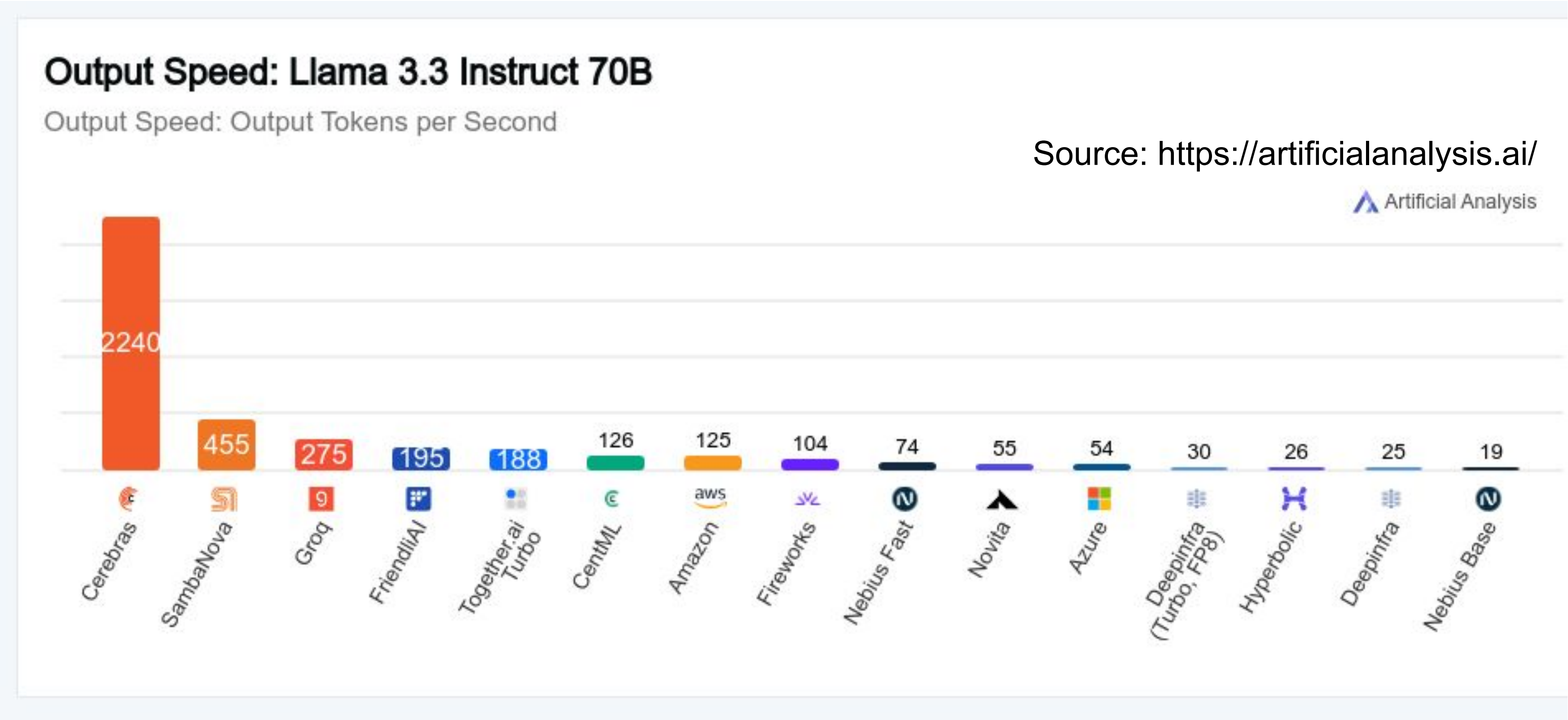




ICYMI: Wafer-Scale Engines make AI go Brrrr…

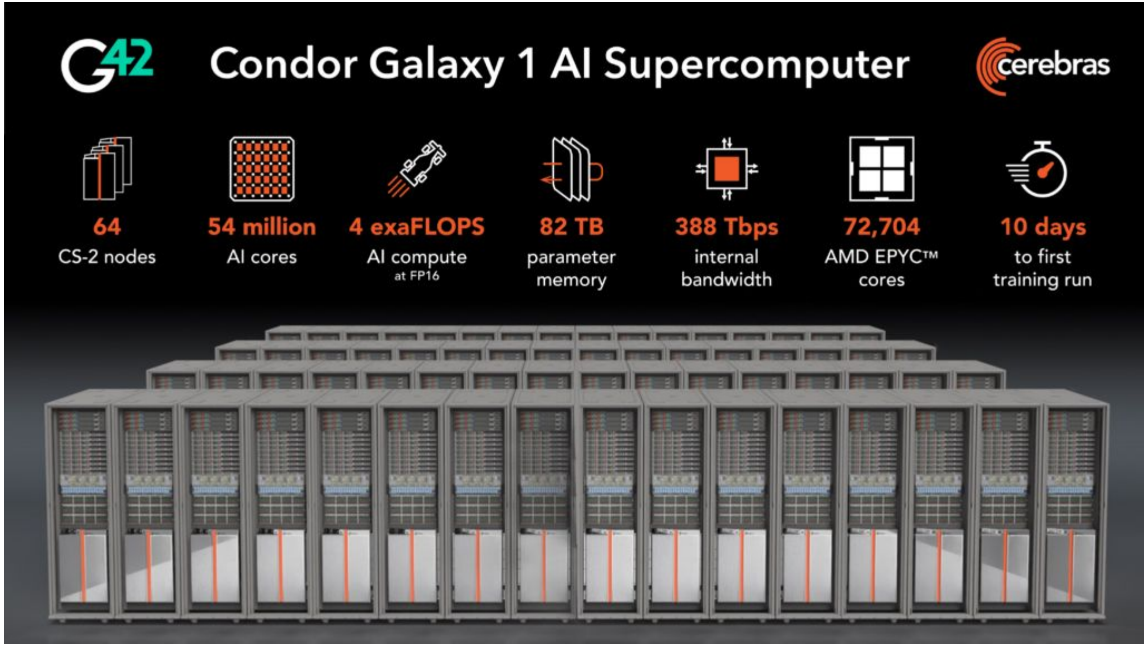


Output Speed: Llama 3.3 Instruct 70B

Output Speed: Output Tokens per Second

Source: https://artificialanalysis.ai/

ICYMI: Cerebras Supercomputers



https://www.cerebras.net/blog/introducing-condor-galaxy-1-a-4-exaflop-supercomputer-for-generative-ai/

ICYMI: The Cerebras Cloud

- 4 ExaFLOPs
- 64 x CS-2s
- 82 TB of Memory

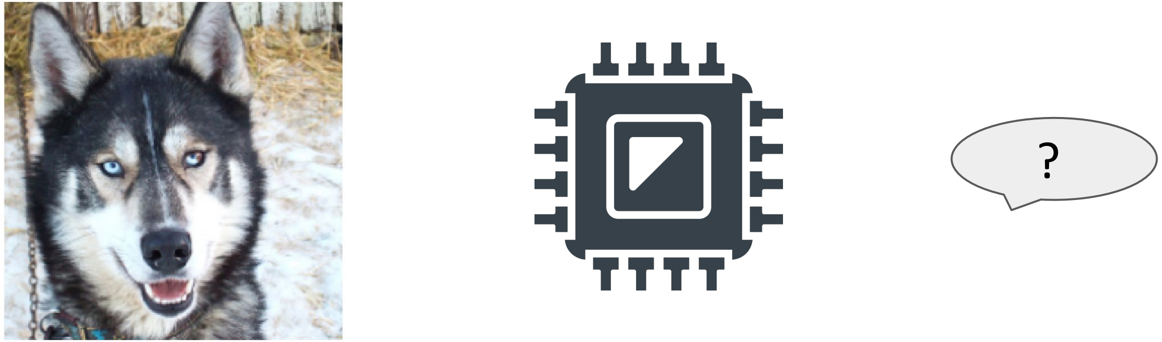
- 4 ExaFLOPs
- 64 x CS-2s
- 82 TB of Memory

- 24 ExaFLOPs
- 192 x CS-3s
- 512 TB of Memory

The AI Decade Speedrun

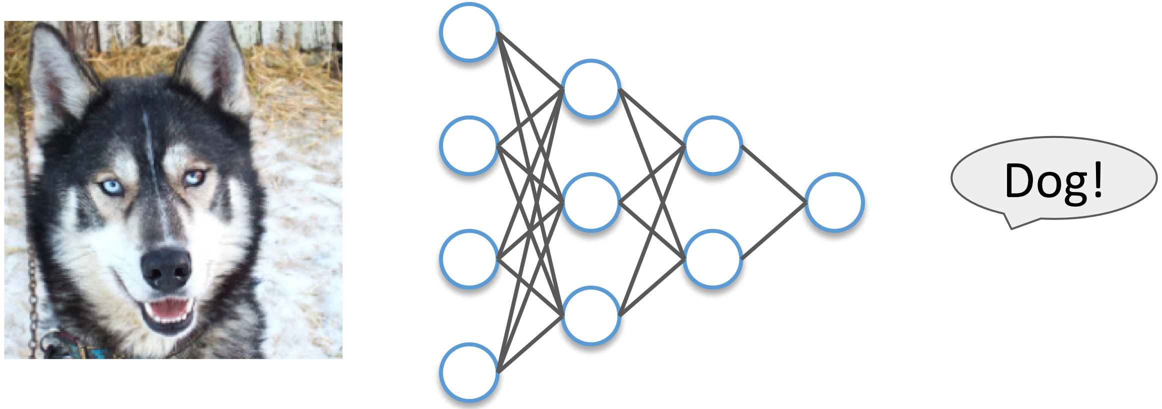
Why CPUs are bad (at AI) and how we got there anyways

Deep Learning



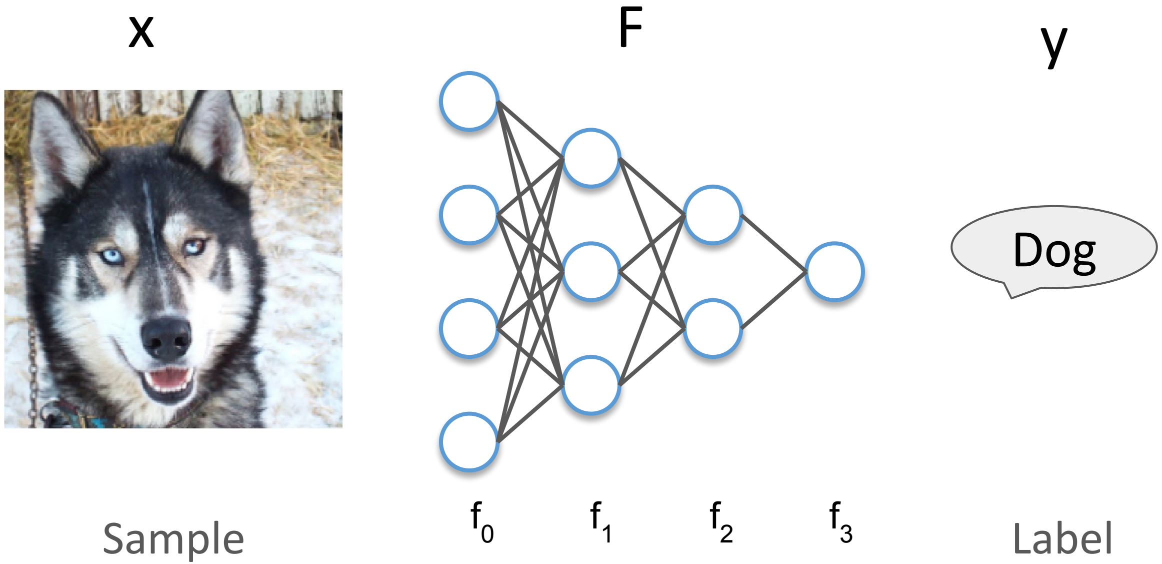
How do we program computers to solve this type of problem?

Deep Learning



Train Neural Networks using Backpropagation!

Deep Learning



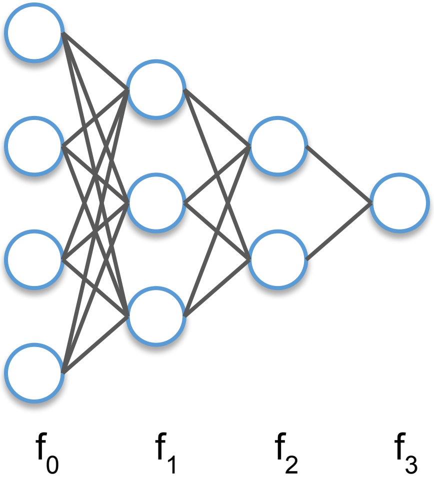
$$F(x) = f_3(f_2(f_1(f_0(x)) = y$$

Deep Learning

x

113	127	164	228
189	237	101	115
076	111	225	192
176	221	242	155
246	164	132	214

F



y

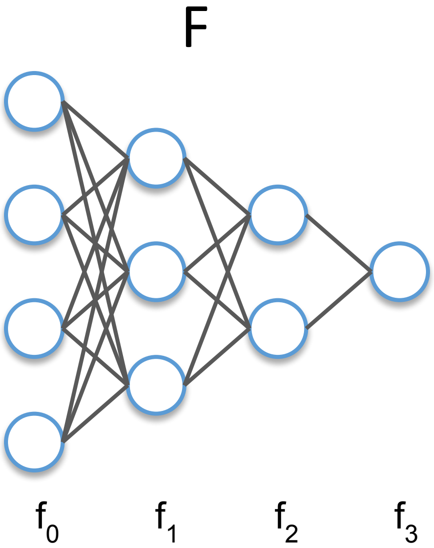
Dog

$$F(x) = f_3(f_2(f_1(f_0(x)) = y$$

Deep Learning

x

113	127	164	228
189	237	101	115
076	111	225	192
176	221	242	155
246	164	132	214



y

0
0
0
1
0
0
0
0
0
0

$$F(x) = f_3(f_2(f_1(f_0(x)) = y$$

Deep Learning

x

113	127	164	228
189	237	101	115
076	111	225	192
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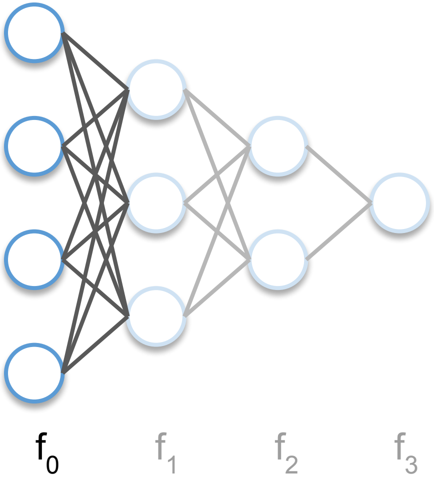

y

0
0
0
1
0
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0

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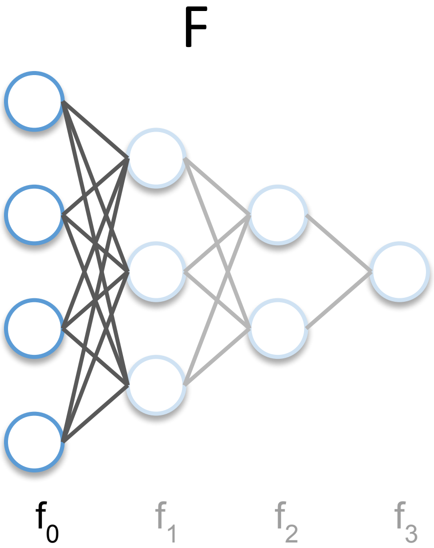


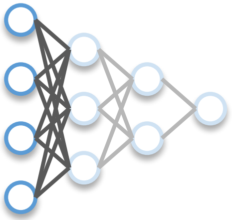
y

0
0
0
1
0
0
0
0
0
0

$f_0(x) = a(W_0 \cdot x + b_0)$ *// In_{f0}= 4, Out_{f0}= 3*

Deep Learning

$$\begin{array}{cccc} W_0 & x & & b_0 \\ \begin{pmatrix} 0.27 & 1.00 & -0.39 & -0.79 \\ 0.60 & 0.19 & -0.26 & -0.48 \\ 0.12 & -0.39 & 0.54 & -0.20 \end{pmatrix} & \begin{pmatrix} 0.68 \\ 0.50 \\ -0.05 \\ 0.11 \end{pmatrix} & + & \begin{pmatrix} 0.31 \\ -0.91 \\ 0.63 \end{pmatrix} \end{array}$$



$$f_0(x) = a(W_0 \cdot x + b_0) \qquad // \; In_{f0} = 4, \; Out_{f0} = 3$$

Deep Learning

$$\begin{array}{cccccc} & W_0 & x & & b_0 & \\ a\,(& \begin{pmatrix} 0.27 & 1.00 & -0.39 & -0.79 \\ 0.60 & 0.19 & -0.26 & -0.48 \\ 0.12 & -0.39 & 0.54 & -0.20 \end{pmatrix} & \begin{pmatrix} 0.68 \\ 0.50 \\ -0.05 \\ 0.11 \end{pmatrix} & + & \begin{pmatrix} 0.31 \\ -0.91 \\ 0.63 \end{pmatrix} &) \end{array}$$

$f_0(x) = a(W_0 \cdot x + b_0)$ $\quad // \; In_{f0} = 4, \; Out_{f0} = 3$

Deep Learning

Model weights will receive gradient updates.

$$a\left(\overset{W_0}{\begin{pmatrix} 0.27 & 1.00 & -0.39 & -0.79 \\ 0.60 & 0.19 & -0.26 & -0.48 \\ 0.12 & -0.39 & 0.54 & -0.20 \end{pmatrix}} \overset{x}{\begin{pmatrix} 0.68 \\ 0.50 \\ -0.05 \\ 0.11 \end{pmatrix}} + \overset{b_0}{\begin{pmatrix} 0.31 \\ -0.91 \\ 0.63 \end{pmatrix}} \right)$$

$f_0(x) = a(W_0 \cdot x + b_0)$ `//` $In_{f0} = 4$, $Out_{f0} = 3$

Deep Learning

```
f = [0 for _ in range(OUT)]
for o in range(OUT):
    for i in range(IN):
        f_0[o] += W[o][i]*x[i]
for o in range(OUT):
    f_0[o] += b[o]
for o in range(OUT):
    f_0[o] = max(0,f[o])
```

$W_0 \cdot x$

$+ b_0$

$a()$

$$f_0(x) = a(W_0 \cdot x + b_0) \qquad // \ \mathit{In}_{f0} = 4, \ \mathit{Out}_{f0} = 3$$

Deep Learning

```
for f_i, f_o, W, b in layers:
    for o in range(len(f_o)):
        for i in range(len(f_i)):
            f_o[o] += W[o][i]*f_i[i]
    for o in range(len(f_o)):
        f_o[o] += b[o]
    for o in range(len(f_o)):
        f_o[o] = max(0,f_o[o])
```

Deep Learning

```
for x in samples:
    for f_i, f_o, W, b in layers:
        for o in range(len(f_o)):
            for i in range(len(f_i)):
                f_o[o] += W[o][i]*f_i[i]
        for o in range(len(f_o)):
            f_o[o] += b[o]
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Deep Learning

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                f_o[o] += b[o]
            for o in range(len(f_o)):
                f_o[o] = max(0,f_o[o])
```

Deep Learning

Weights will be used in the forward pass and receive gradient updates in the backward pass.

```
for _ in epochs:
    for x in samples:
        for f_i, f_o, W, b in layers:
            for o in range(len(f_o)):
                for i in range(len(f_i)):
                    f_o[o] += W[o][i]*f_i[i]
            for o in range(len(f_o)):
                f_o[o] += b[o]
            for o in range(len(f_o)):
                f_o[o] = max(0,f_o[o])
```

The inner loop over the samples only shows the Forward pass,
a full cycle includes auto-generated Backward and Optimizer computation.

Deep Learning

```
for _ in epochs:
    for x in samples:
        for f_i, f_o, W, b in layers:
            for o in range(len(f_o)):
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            for o in range(len(f_o)):
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```

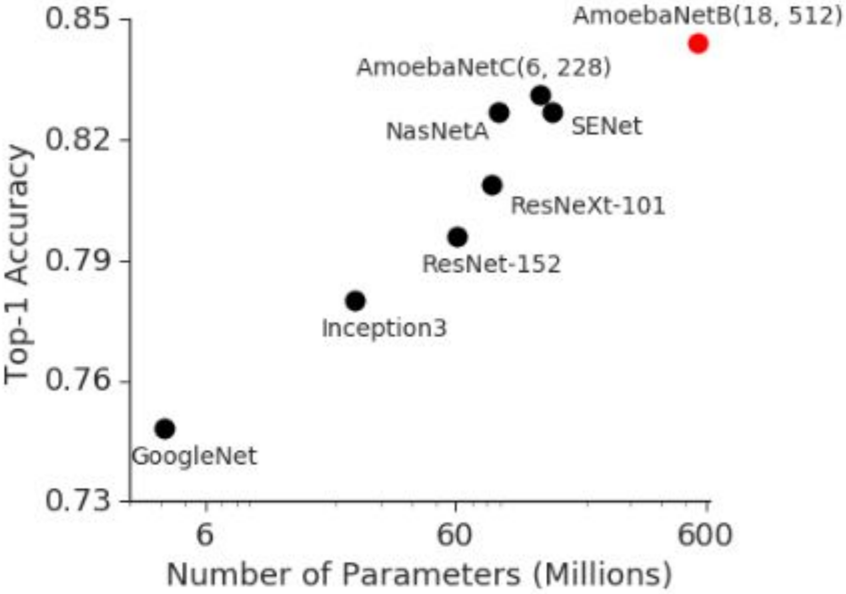
e.g., 100 epochs, 1M samples, 100 layers, dims 2 to 2^{16}

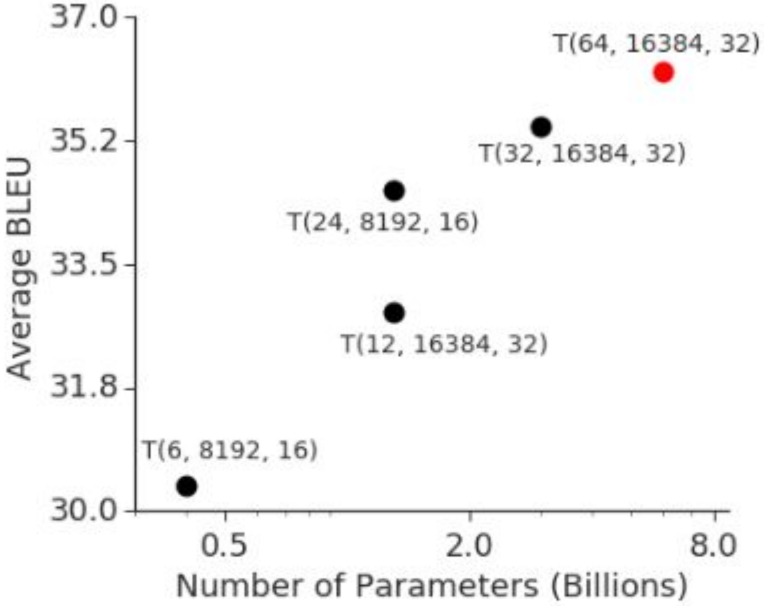
Deep Learning

```
for _ in epochs:
    for x in samples:
        for f_i, f_o, W, b in layers:
            for o in range(len(f_o)):
                for i in range(len(f_i)):
                    f_o[o] += W[o][i]*f_i[i]
            for o in range(len(f_o)):
                f_o[o] += b[o]
            for o in range(len(f_o)):
                f_o[o] = max(0,f_o[o])
```

~ 2025 SOTA Workloads: ***10^{21} to 10^{24} FLOPs***

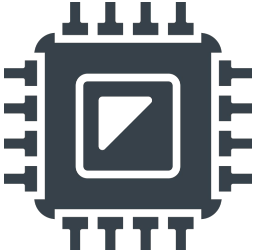
Deep Learning

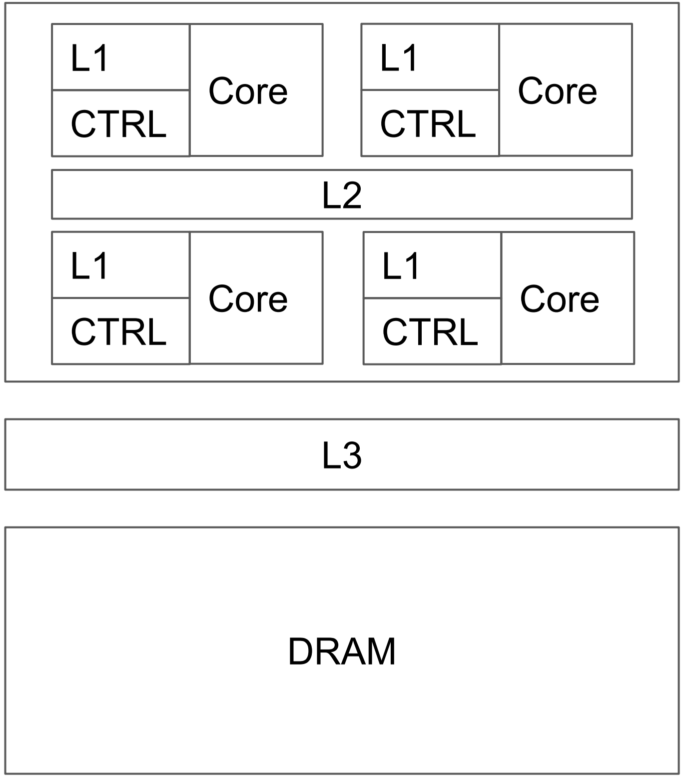




[1] GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism - Huang, et al., NeurIPS, 2019.

Target Architecture: CPU





L1
CTRL
Core

L1
CTRL
Core

L2

L1
CTRL
Core

L1
CTRL
Core

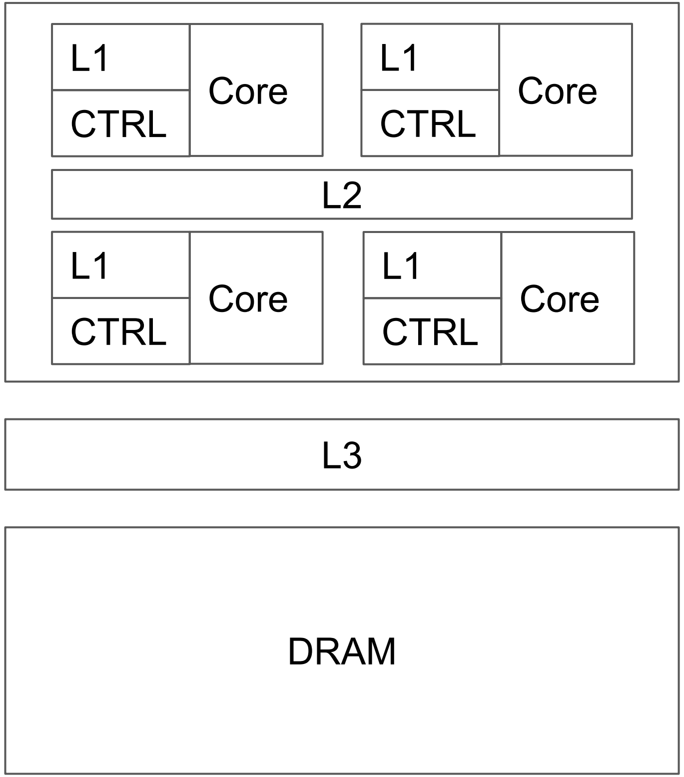
L3

DRAM

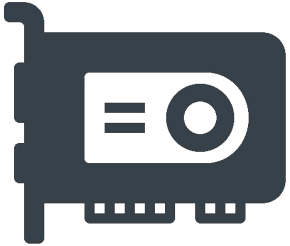
Target Architecture: CPU

- 4-32 “big” cores (8-64 threads)
- 128 GB Memory
- 2 TFLOPS peak
- Powerful OoO Engine
  - Branch Predictors
  - Prefetching
  - Reordering
  - Speculation
- Complex caches
- 100 GB/s memory bandwidth

Key Metric: **Integer** Performance!



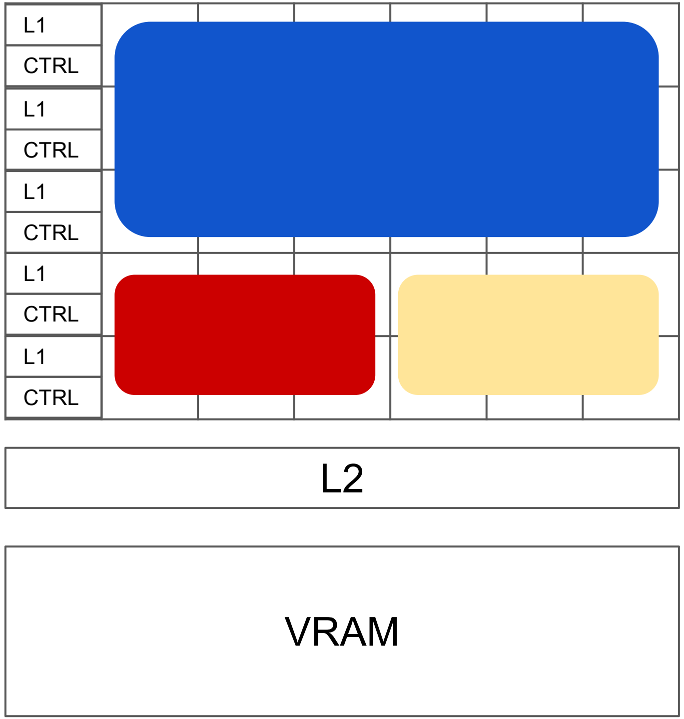
Target Architecture: GPU



```
for _ in epochs:
    for x in samples:
        for f_i, f_o, W, b in layers:
            for o in range(len(f_o)):
                for i in range(len(f_i)):
                    f_o[o] += W[o][i]*f_i[i]
            for o in range(len(f_o)):
                f_o[o] += b[o]
            for o in range(len(f_o)):
                f_o[o] = max(0,f_o[o])
```

Kernels

Target Architecture: GPU



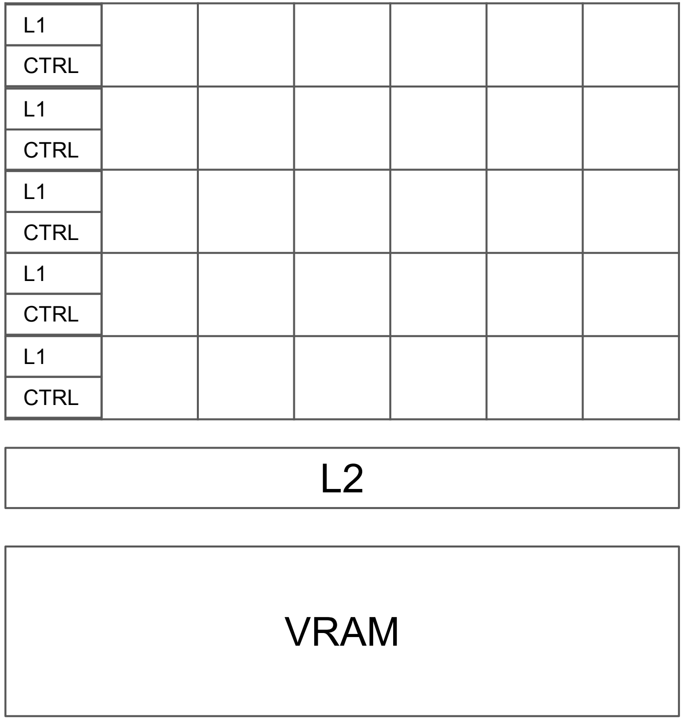
L1
CTRL
L1
CTRL
L1
CTRL
L1
CTRL
L1
CTRL

L2

VRAM

Target Architecture: GPU

- 1000 cores
- 16 GB Memory
- 125 TFLOPS peak
- Groups of small cores execute the same operation on different data in lockstep
- 900 GB/s memory bandwidth



Target Architecture: GPU

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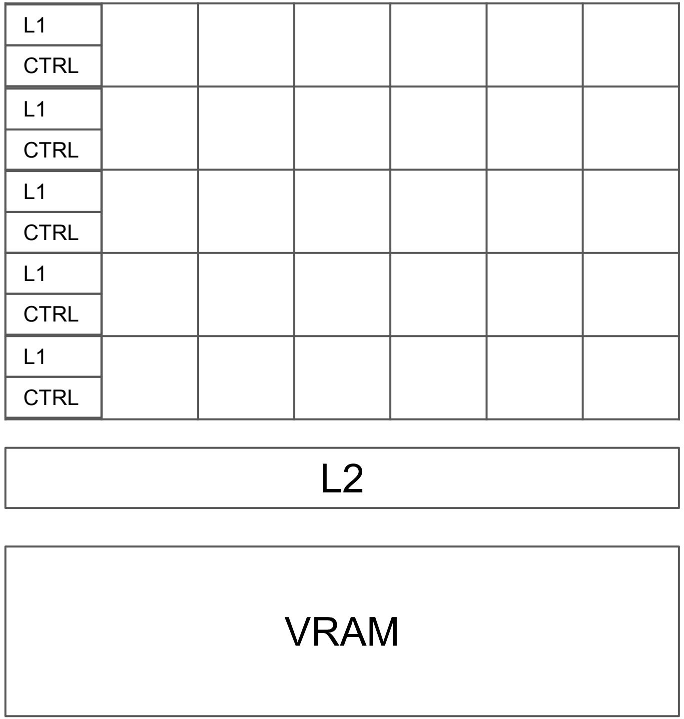
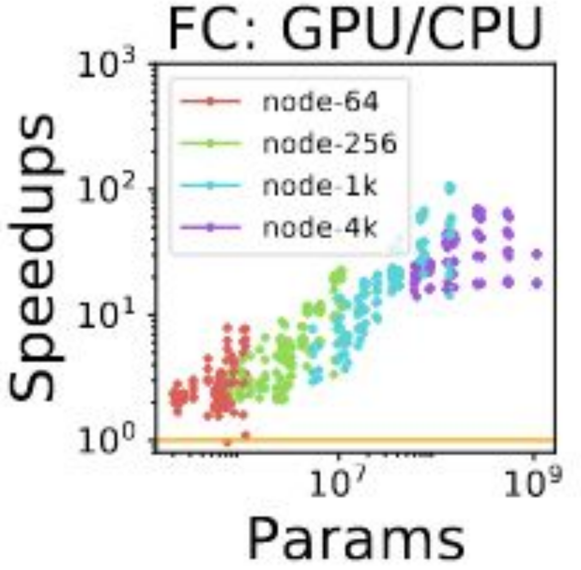
Key Metric: **Floating Point** Performance!



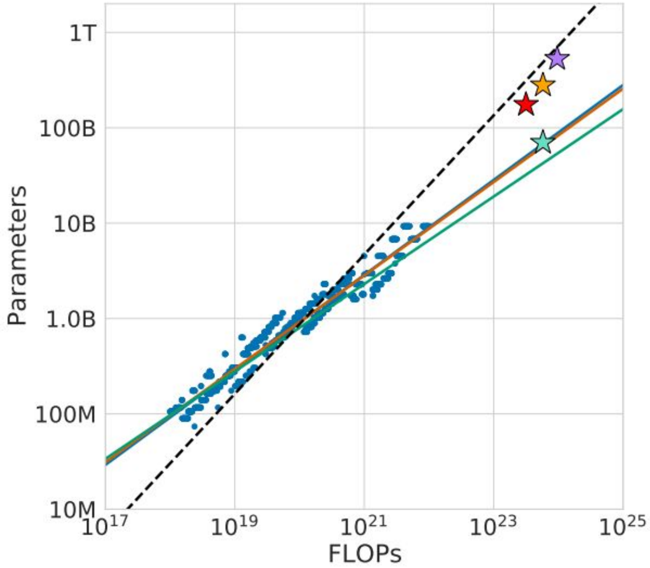
Speedup Comparison



(b) Node

[2] Wang, Yu Emma, Gu-Yeon Wei, and David Brooks. Figure 9 in "Benchmarking TPU, GPU, and CPU platforms for deep learning." Preprint on arXiv, 2019.

The Cost of Training



$$L(N,D) = \underbrace{\frac{A}{N^{\alpha}}}_{\text{finite model}} + \underbrace{\frac{B}{D^{\beta}}}_{\text{finite data}} + \underbrace{E}_{\text{irreducible}}$$

5) Scaling Laws for Neural Language Models - Kaplan, et al., Preprint on Arxiv, 2020.

6) Training Compute-Optimal Large Language Models - Hoffmann, Borgeaud, Mensch, et al., Preprint on Arxiv, 2022.

The Cost of Training

Starts at $10M

$$L(N,D) = \underbrace{\frac{A}{N^{\alpha}}}_{\text{finite model}} + \underbrace{\frac{B}{D^{\beta}}}_{\text{finite data}} + \underbrace{E}_{\text{irreducible}}$$

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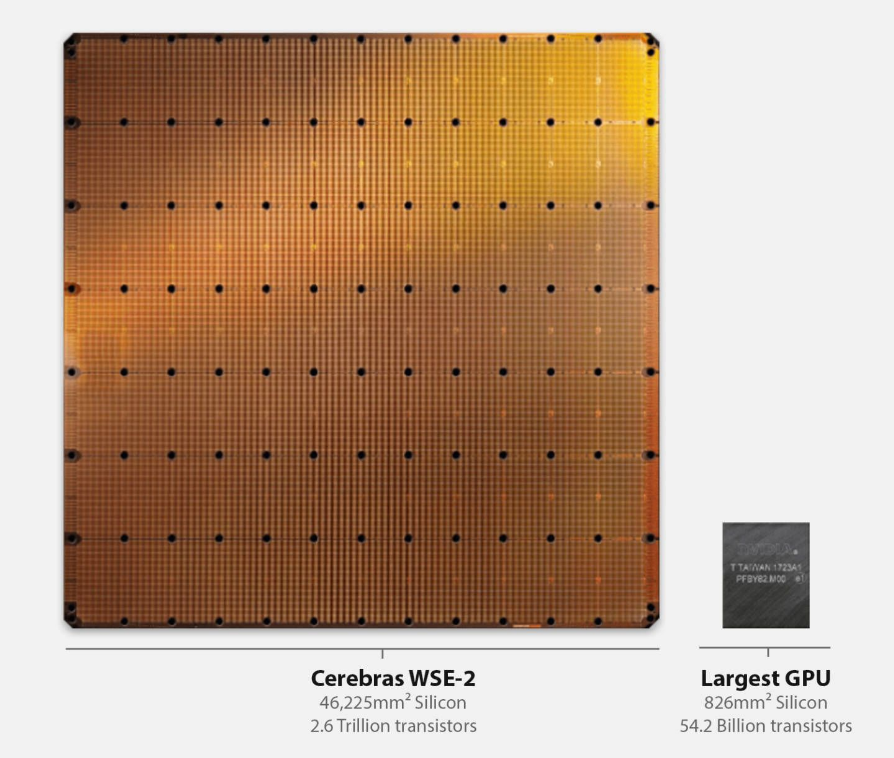
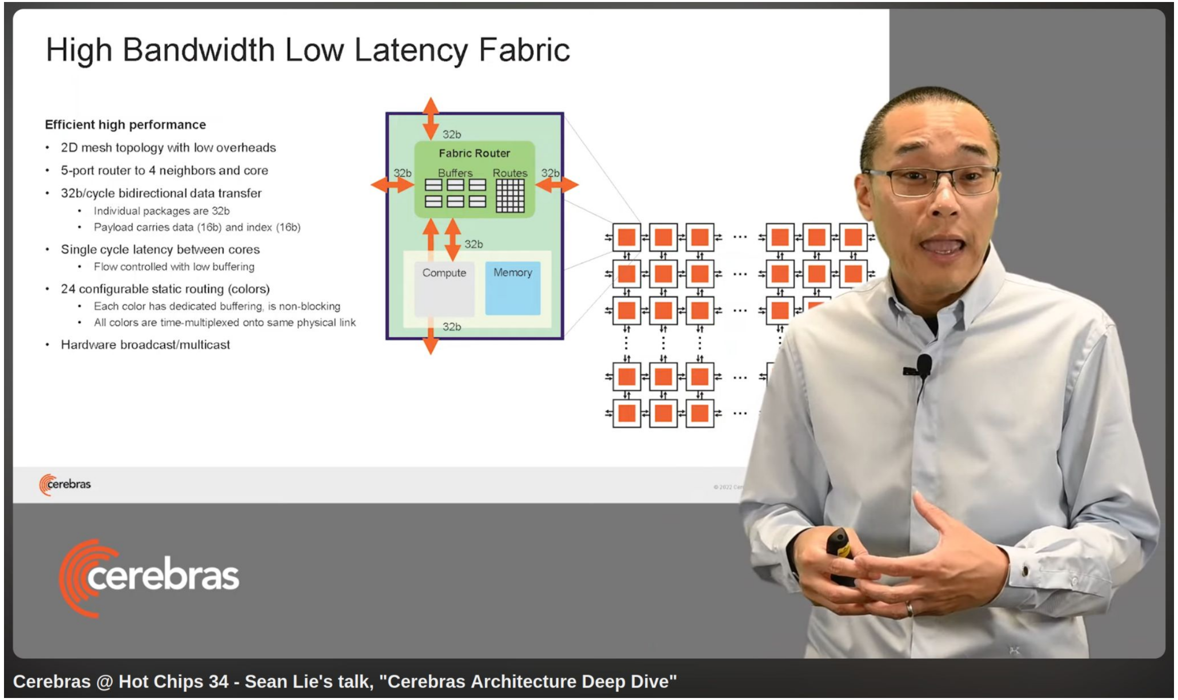
(7) https://en.wikipedia.org/wiki/FLOPS#Hardware_costs (retrieved January 2025).

Target Architecture: The Cerebras Wafer-Scale Engine

- 850k cores
- 40G cache
- 20 PB/s bandwidth
- TBs of RAM
- On-fabric mesh to route data connections between cores



Target Architecture: The Cerebras Wafer-Scale Engine



High Bandwidth Low Latency Fabric

Efficient high performance

- 2D mesh topology with low overheads
- 5-port router to 4 neighbors and core
- 32b/cycle bidirectional data transfer
  - Individual packages are 32b
  - Payload carries data (16b) and index (16b)
- Single cycle latency between cores
  - Flow controlled with low buffering
- 24 configurable static routing (colors)
  - Each color has dedicated buffering, is non-blocking
  - All colors are time-multiplexed onto same physical link
- Hardware broadcast/multicast

Cerebras @ Hot Chips 34 - Sean Lie's talk, "Cerebras Architecture Deep Dive"

https://www.youtube.com/watch?v=8i1_Ru5siXc

2012
First port to GPUs(3)

2014
Initial cuDNN Release(4)

2015
Cerebras Systems,
Qualcomm Snapdragon Neural Processing Engine,
Tensorflow

2016
PyTorch, Google TPU,
NVIDIA DGX,
Apple Neural Engine

2019
Wafer-Scale Engine,
LLVM MLIR,
OpenAI Triton

2022
ChatGPT

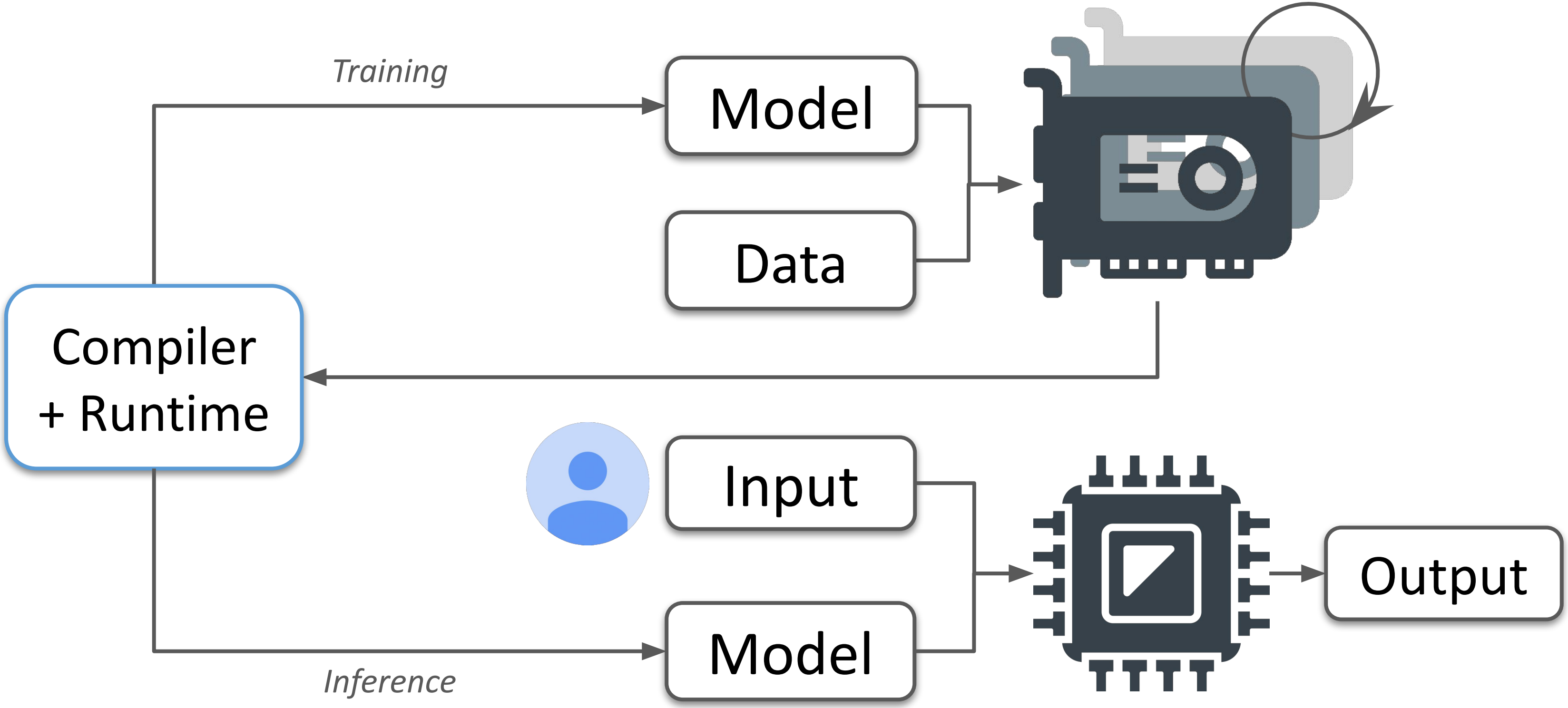
3) Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. Imagenet classification with deep convolutional neural networks. In NIPS, pages 1106–1114, 2012.

4) cuDNN: Efficient Primitives for Deep Learning - Sharan Chetlur, Cliff Woolley, Philippe Vandermersch, Jonathan Cohen, John Tran, Bryan Catanzaro, Evan Shelhamer. Preprint on Arxiv, 2014.

A Golden Age of Compilers?

“The Golden Age of Compiler Design in an Era of HW/SW Co-design”
ASPLOS Keynote 2021 by Chris Lattner
https://www.youtube.com/watch?v=4HgShra-KnY

Training vs. Inference in an AoT Compiler Workflow



Typical AOT Overview

PyTorch

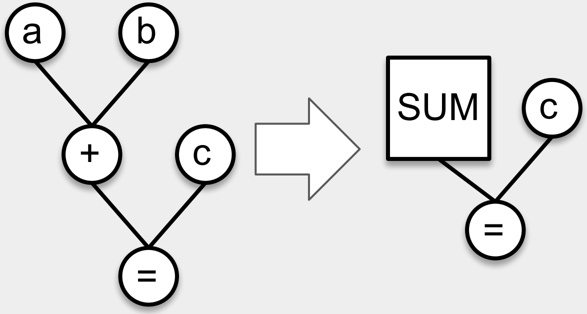
API

Autograd

Graph Capture

LLVM MLIR

Analysis & Transformation



Runtime

Cluster Services

Optimizers

Kernels

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PyTorch

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- Autograd
- Graph Capture

LLVM MLIR

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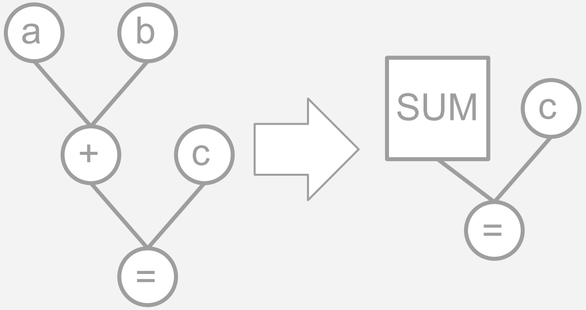


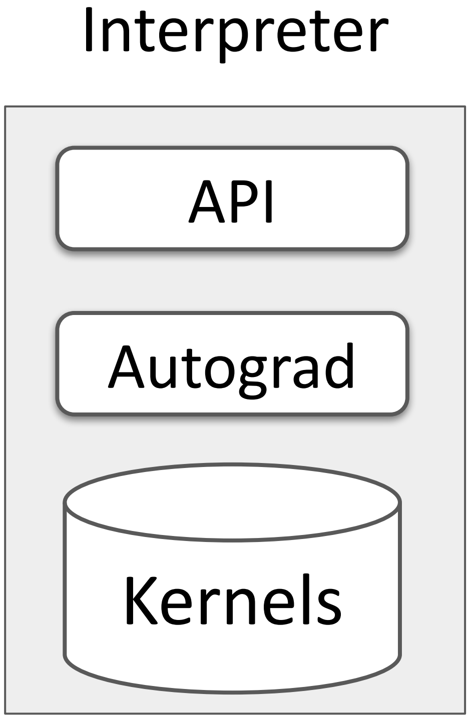
Runtime

- Cluster Services
- Optimizers
- Kernels

PyTorch - API

Python-based API, C++ library

- Interpreter with pre-defined native kernels (“Eager Execution”)
- Target Focus: CPUs, GPUs
- Ongoing efforts to develop a Just-in-Time engine
    - ○ has proven challenging



PyTorch - Tensors, Autograd

Central data type: torch.Tensor

- Wraps “ATen” classes
    - Essentially a general purpose & fast linear algebra library
- N-Dimensional
- Dynamic dispatch
- Support structure for reverse-mode auto differentiation

Tensor types

shape

dtype

device

grad_

PyTorch - Tensors, Autograd

```
>>> t = torch.tensor([[1,2,3],[4,5,6]], dtype=torch.float,
                         device='cpu', requires_grad=True)
>>> t
tensor([[1., 2., 3.], [4., 5., 6.]], requires_grad=True)
>>> t.shape
torch.Size([2, 3])
```

Tensor types

shape

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Tensor types

shape

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grad_

Recommended Reading: https://github.com/karpathy/micrograd
http://blog.ezyang.com/2019/05/pytorch-internals/

Graph Capture

- How can we turn this into a graph we can compile ahead of time?

```
class HelloNNWorld(nn.Module):
    from nn.functional import relu
    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = x.flatten(start_dim=1)
        x = self.linear(x)
        return relu(x)

def train(input, model, loss_fn, optimizer):
    model.train()
    for (X, y) in input:
        pred = model(X)
        loss = loss_fn(pred, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

Graph Capture

- How can we turn this into a graph we can compile ahead of time?

- **Tracing!**

```
class HelloNNWorld(nn.Module):
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    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = x.flatten(start_dim=1)
        x = self.linear(x)
        return relu(x)

def train(input, model, loss_fn, optimizer):
    model.train()
    for (X, y) in input:
        pred = model(X)
        loss = loss_fn(pred, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```
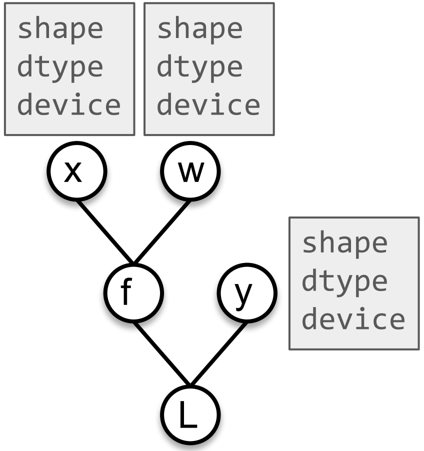

Graph Capture

```
class HelloNNWorld(nn.Module):
    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = torch.flatten(x, start_dim=1)
        x = self.linear(x)
        return nn.functional.relu(x)

def train(input, model, loss_fn, optimizer):
    model.train()
    for (X, y) in input:
        pred = model(X)
        loss = loss_fn(pred, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```



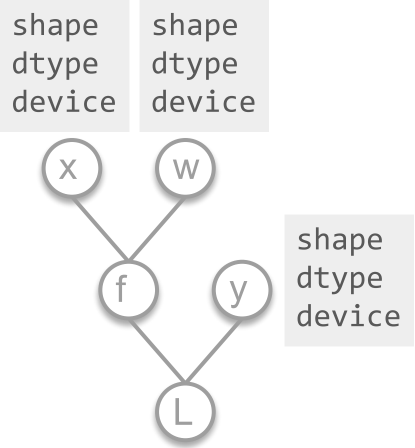
shape
dtype
device

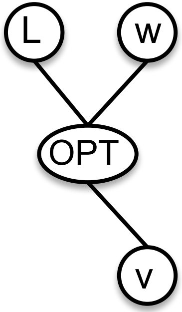
shape
dtype
device

shape
dtype
device

Graph Capture

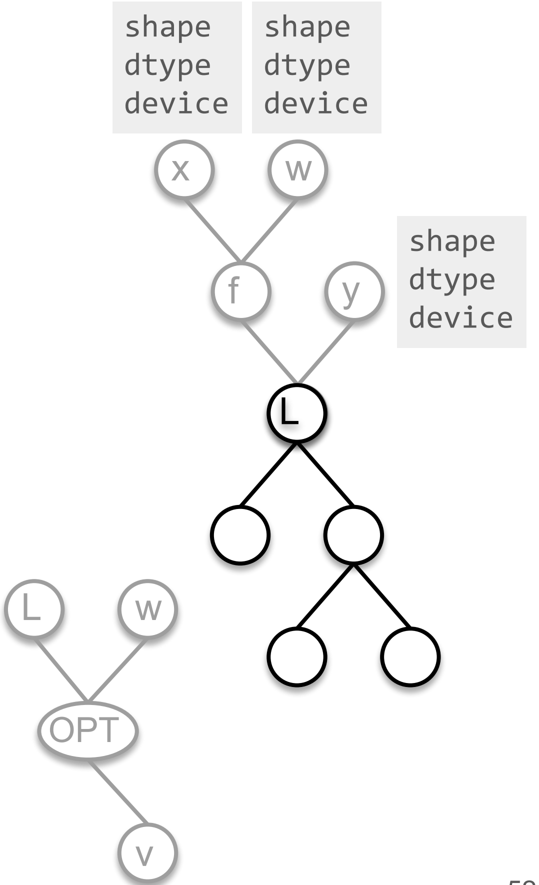
```
class HelloNNWorld(nn.Module):
    from nn.functional import relu
    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = x.flatten(start_dim=1)
        x = self.linear(x)
        return relu(x)

def train(input, model, loss_fn, optimizer):
    model.train()
    for (X, y) in input:
        pred = model(X)
        loss = loss_fn(pred, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```





Graph Capture

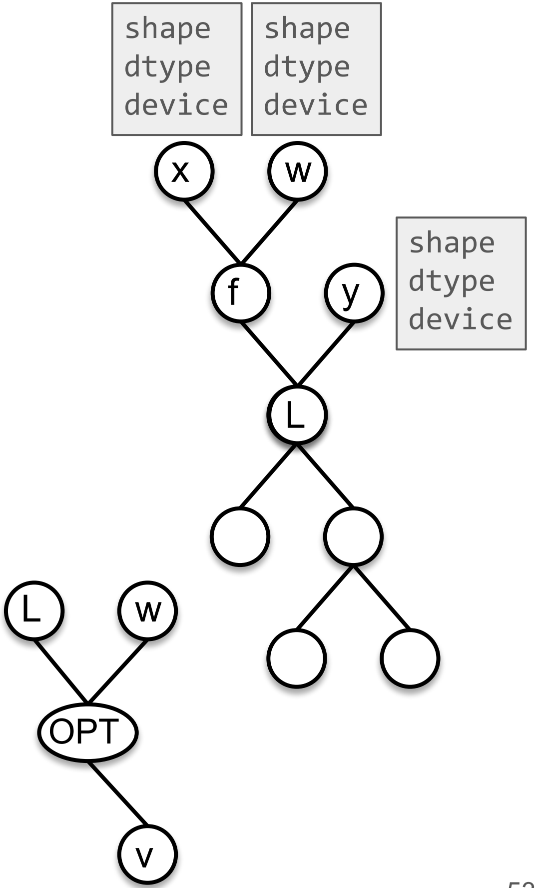
```
class HelloNNWorld(nn.Module):
    from nn.functional import relu
    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = x.flatten(start_dim=1)
        x = self.linear(x)
        return relu(x)

def train(input, model, loss_fn, optimizer):
    model.train()
    for (X, y) in input:
        pred = model(X)
        loss = loss_fn(pred, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```



Graph Capture

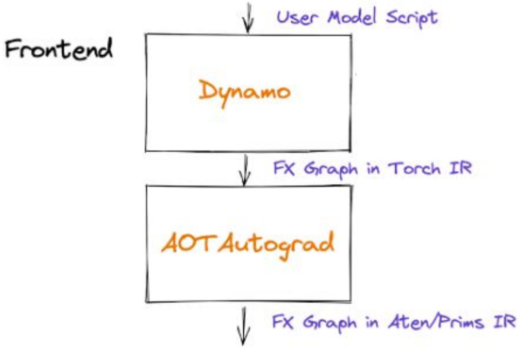
Several ways to implement tracing

- Dynamo
  - parses Python stack
  - can capture non-PyTorch code
- Lazy Tensor Core (LTC)
  - instantiates all values on a “fake” device
  - only records PyTorch API accesses



Graph Capture using Dynamo

```
class HelloNNWorld(nn.Module):
    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = torch.flatten(x, start_dim=1)
        x = self.linear(x)
        return nn.functional.relu(x)
```



https://pytorch.org/get-started/pytorch-2.0

```
forward():
    empty  = torch.ops.aten.empty.memory_format([10, 784], device = device(type='cpu'), pin_memory = False)
    detach = torch.ops.aten.detach.default(empty)
    detach_1 = torch.ops.aten.detach.default(detach)
    empty_1  = torch.ops.aten.empty.memory_format([10], device = device(type='cpu'), pin_memory = False)
    detach_2 = torch.ops.aten.detach.default(empty_1)
    detach_3 = torch.ops.aten.detach.default(detach_2)
    uniform_ = torch.ops.aten.uniform_.default(detach_1, -0.03571428571428571, 0.03571428571428571)
    uniform__1 = torch.ops.aten.uniform_.default(detach_3, -0.03571428571428571, 0.03571428571428571)
    view = torch.ops.aten.view.default(arg0_1, [16, 784])
    t = torch.ops.aten.t.default(uniform_)
    addmm = torch.ops.aten.addmm.default(uniform__1, view, t)
    relu = torch.ops.aten.relu.default(addmm)
    return relu
```

Graph Capture

```
class HelloNNWorld(nn.Module):
    def __init__(self, H=28, W=28, C=10):
        super(HelloNNWorld, self).__init__()
        self.linear = nn.Linear(H*W, C)
    def forward(self, x):
        x = torch.flatten(x, start_dim=1)
        x = self.linear(x)
        return nn.functional.relu(x)

def train(input, model, loss_fn, optimizer):
    model.train()
    for (X, y) in input:
        pred = model(X)
        loss = loss_fn(pred, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

Graph Capture

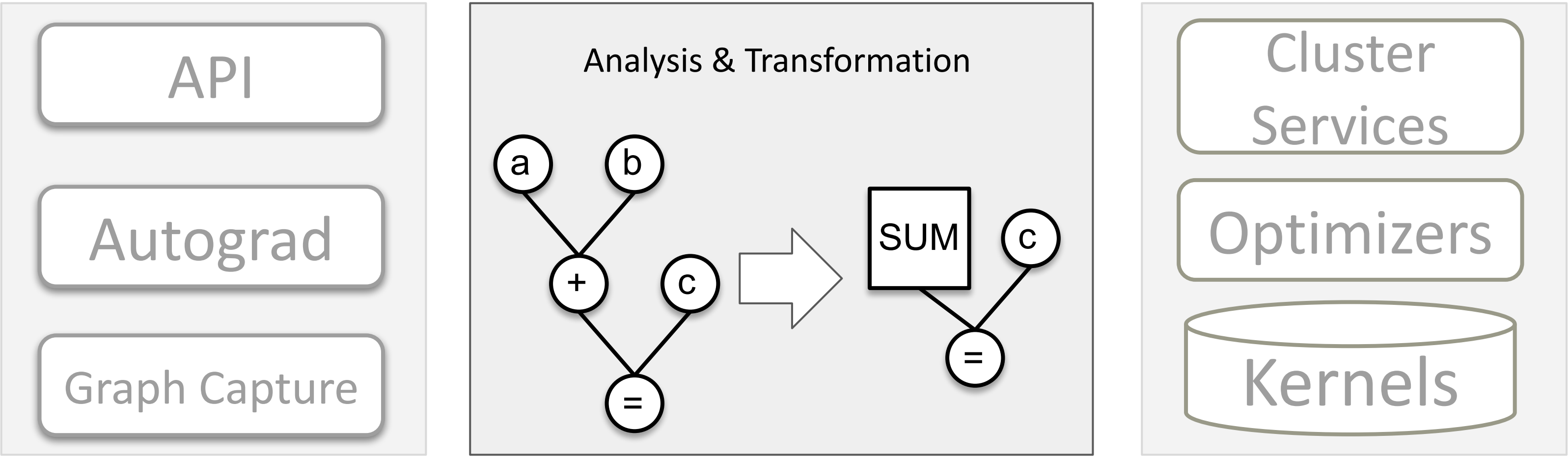
```
forward+loss+backward():
    empty  = torch.ops.aten.empty.memory_format([10, 784], device = device(type='cpu'), pin_memory = False)
    detach = torch.ops.aten.detach.default(empty)
    detach_1 = torch.ops.aten.detach.default(detach)
    empty_1  = torch.ops.aten.empty.memory_format([10], device = device(type='cpu'), pin_memory = False)
    detach_2 = torch.ops.aten.detach.default(empty_1)
    detach_3 = torch.ops.aten.detach.default(detach_2)
    uniform_ = torch.ops.aten.uniform_.default(detach_1, -0.03571428571428571, 0.03571428571428571)
    uniform__1 = torch.ops.aten.uniform_.default(detach_3, -0.03571428571428571, 0.03571428571428571)
    view = torch.ops.aten.view.default(arg0_1, [16, 784])
    t = torch.ops.aten.t.default(uniform_)
    addmm = torch.ops.aten.addmm.default(uniform__1, view, t)
    relu = torch.ops.aten.relu.default(addmm)
    detach_4 = torch.ops.aten.detach.default(relu)
    _log_softmax = torch.ops.aten._log_softmax.default(relu, 1, False)
    detach_5 = torch.ops.aten.detach.default(_log_softmax)
    nll_loss_forward = torch.ops.aten.nll_loss_forward.default(_log_softmax, arg1_1, None, 1, -100)
    getitem = nll_loss_forward[0]
    getitem_1 = nll_loss_forward[1]
```

Graph Capture

```
ones_like = torch.ops.aten.ones_like.default(getitem, dtype = torch.float32, layout = torch.strided,
              device = device(type='cpu'), pin_memory = False, memory_format = torch.preserve_format)
nll_loss_backward = torch.ops.aten.nll_loss_backward.default(ones_like, _log_softmax, arg1_1, None, 1,
                      -100, getitem_1)
detach_6 = torch.ops.aten.detach.default(detach_5)
_log_softmax_backward_data = torch.ops.aten._log_softmax_backward_data.default(nll_loss_backward,
                               detach_6, 1, torch.float32)
detach_7 = torch.ops.aten.detach.default(detach_4)
threshold_backward = torch.ops.aten.threshold_backward.default(_log_softmax_backward_data, detach_7, 0)
t_1 = torch.ops.aten.t.default(threshold_backward)
mm = torch.ops.aten.mm.default(t_1, view)
t_2 = torch.ops.aten.t.default(mm)
sum_1 = torch.ops.aten.sum.dim_IntList(threshold_backward, [0], True)
view_1 = torch.ops.aten.view.default(sum_1, [10])
detach_8 = torch.ops.aten.detach.default(view_1)
detach_9 = torch.ops.aten.detach.default(detach_8)
t_3 = torch.ops.aten.t.default(t_2)
detach_10 = torch.ops.aten.detach.default(t_3)
detach_11 = torch.ops.aten.detach.default(detach_10)
return [getitem]
```

Deep Learning Compilers

LLVM MLIR



API

Autograd

Graph Capture

Analysis & Transformation

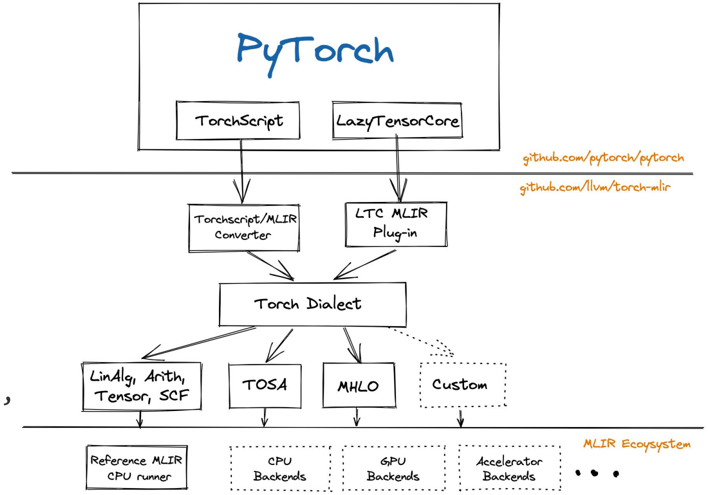
Cluster Services

Optimizers

Kernels

LLVM MLIR!

https://github.com/llvm/torch-mlir



```
module attributes {torch.debug_module_name = "GraphModule"} {
  func.func @forward(
     %arg0: !torch.vtensor<[10,784],f32>,
     %arg1: !torch.vtensor<[10],f32>,
     %arg2: !torch.vtensor<[16,28,28],f32>) -> (!torch.vtensor<[16,10],f32>,
            !torch.vtensor<[16,784],f32>,!torch.vtensor<[16,10],f32>)
  {
    %int0   = torch.constant.int 0
    %int1   = torch.constant.int 1
    %int784 = torch.constant.int 784
    %int16  = torch.constant.int 16
    %0 = torch.prim.ListConstruct %int16, %int784 : (!torch.int, !torch.int) -> !torch.list<int>
    %1 = torch.aten.view %arg2, %0 : !torch.vtensor<[16,28,28],f32>, !torch.list<int> -> !torch.vtensor<[16,784],f32>
    %2 = torch.aten.transpose.int %arg0, %int0, %int1 : !torch.vtensor<[10,784],f32>, !torch.int, !torch.int
                                                     -> !torch.vtensor<[784,10],f32>
    %3 = torch.aten.mm %1, %2 : !torch.vtensor<[16,784],f32>, !torch.vtensor<[784,10],f32> -> !torch.vtensor<[16,10],f32>
    %4 = torch.aten.mul.Scalar %arg1, %int1 : !torch.vtensor<[10],f32>, !torch.int -> !torch.vtensor<[10],f32>
    %5 = torch.aten.add.Tensor %4, %3, %int1 : !torch.vtensor<[10],f32>, !torch.vtensor<[16,10],f32>, !torch.int
                                            -> !torch.vtensor<[16,10],f32>
    %6 = torch.aten.relu %5 : !torch.vtensor<[16,10],f32> -> !torch.vtensor<[16,10],f32>
    return %6, %1, %6 : !torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>, !torch.vtensor<[16,10],f32>
  }
}
```

MLIR - Textual Format

```
module attributes {torch.debug_module_name = "GraphModule"} {
  func.func @forward(
     %arg0: !torch.vtensor<[10,784],f32>,
     %arg1: !torch.vtensor<[10],f32>,
     %arg2: !torch.vtensor<[16,28,28],f32>
  ) -> (!torch.vtensor<[16,10],f32>,!torch.vtensor<[16,784],f32>,!torch.vtensor<[16,10],f32>)
  {
    %int0   = torch.constant.int 0
    %int1   = torch.constant.int 1
    %int784 = torch.constant.int 784
    %int16  = torch.constant.int 16
    %0 = torch.prim.ListConstruct %int16, %int784 : (!torch.int, !torch.int) -> !torch.list<int>
    %1 = torch.aten.view %arg2, %0 : !torch.vtensor<[16,28,28],f32>, !torch.list<int> -> !torch.vtensor<[16,784],f32>
    %2 = torch.aten.transpose.int %arg0, %int0, %int1 : !torch.vtensor<[10,784],f32>, !torch.int, !torch.int
                                                     -> !torch.vtensor<[784,10],f32>
    %3 = torch.aten.mm %1, %2 : !torch.vtensor<[16,784],f32>, !torch.vtensor<[784,10],f32> -> !torch.vtensor<[16,10],f32>
    %4 = torch.aten.mul.Scalar %arg1, %int1 : !torch.vtensor<[10],f32>, !torch.int -> !torch.vtensor<[10],f32>
    %5 = torch.aten.add.Tensor %4, %3, %int1 : !torch.vtensor<[10],f32>, !torch.vtensor<[16,10],f32>, !torch.int
                                            -> !torch.vtensor<[16,10],f32>
    %6 = torch.aten.relu %5 : !torch.vtensor<[16,10],f32> -> !torch.vtensor<[16,10],f32>
    return %6, %1, %6 : !torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>, !torch.vtensor<[16,10],f32>
  }
}
```

MLIR - Modules, Functions

```
module attributes {torch.debug_module_name = "GraphModule"} {
  func.func @forward(
     %arg0: !torch.vtensor<[10,784],f32>,
     %arg1: !torch.vtensor<[10],f32>,
     %arg2: !torch.vtensor<[16,28,28],f32>
  ) -> (!torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>,!torch.vtensor<[16,10],f32>)
  {
    %int0   = torch.constant.int 0
    %int1   = torch.constant.int 1
    %int784 = torch.constant.int 784
    %int16  = torch.constant.int 16
    %0 = torch.prim.ListConstruct %int16, %int784 : (!torch.int, !torch.int) -> !torch.list<int>
    %1 = torch.aten.view %arg2, %0 : !torch.vtensor<[16,28,28],f32>, !torch.list<int> -> !torch.vtensor<[16,784],f32>
    %2 = torch.aten.transpose.int %arg0, %int0, %int1 : !torch.vtensor<[10,784],f32>, !torch.int, !torch.int
                                                     -> !torch.vtensor<[784,10],f32>
    %3 = torch.aten.mm %1, %2 : !torch.vtensor<[16,784],f32>, !torch.vtensor<[784,10],f32> -> !torch.vtensor<[16,10],f32>
    %4 = torch.aten.mul.Scalar %arg1, %int1 : !torch.vtensor<[10],f32>, !torch.int -> !torch.vtensor<[10],f32>
    %5 = torch.aten.add.Tensor %4, %3, %int1 : !torch.vtensor<[10],f32>, !torch.vtensor<[16,10],f32>, !torch.int
                                            -> !torch.vtensor<[16,10],f32>
    %6 = torch.aten.relu %5 : !torch.vtensor<[16,10],f32> -> !torch.vtensor<[16,10],f32>
    return %6, %1, %6 : !torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>, !torch.vtensor<[16,10],f32>
  }
}
```

MLIR - Types

```
module attributes {torch.debug_module_name = "GraphModule"} {
  func.func @forward(
     %arg0: !torch.vtensor<[10,784],f32>,
     %arg1: !torch.vtensor<[10],f32>,
     %arg2: !torch.vtensor<[16,28,28],f32>
  ) -> (!torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>,!torch.vtensor<[16,10],f32>)
  {
    %int0   = torch.constant.int 0
    %int1   = torch.constant.int 1
    %int784 = torch.constant.int 784
    %int16  = torch.constant.int 16
    %0 = torch.prim.ListConstruct %int16, %int784 : (!torch.int, !torch.int) -> !torch.list<int>
    %1 = torch.aten.view %arg2, %0 : !torch.vtensor<[16,28,28],f32>, !torch.list<int> -> !torch.vtensor<[16,784],f32>
    %2 = torch.aten.transpose.int %arg0, %int0, %int1 : !torch.vtensor<[10,784],f32>, !torch.int, !torch.int
                                                     -> !torch.vtensor<[784,10],f32>
    %3 = torch.aten.mm %1, %2 : !torch.vtensor<[16,784],f32>, !torch.vtensor<[784,10],f32> -> !torch.vtensor<[16,10],f32>
    %4 = torch.aten.mul.Scalar %arg1, %int1 : !torch.vtensor<[10],f32>, !torch.int -> !torch.vtensor<[10],f32>
    %5 = torch.aten.add.Tensor %4, %3, %int1 : !torch.vtensor<[10],f32>, !torch.vtensor<[16,10],f32>, !torch.int
                                            -> !torch.vtensor<[16,10],f32>
    %6 = torch.aten.relu %5 : !torch.vtensor<[16,10],f32> -> !torch.vtensor<[16,10],f32>
    return %6, %1, %6 : !torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>, !torch.vtensor<[16,10],f32>
  }
}
```

MLIR - Operations

```
module attributes {torch.debug_module_name = "GraphModule"} {
  func.func @forward(
     %arg0: !torch.vtensor<[10,784],f32>,
     %arg1: !torch.vtensor<[10],f32>,
     %arg2: !torch.vtensor<[16,28,28],f32>
  ) -> (!torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>,!torch.vtensor<[16,10],f32>)
  {
    %int0   = torch.constant.int 0
    %int1   = torch.constant.int 1
    %int784 = torch.constant.int 784
    %int16  = torch.constant.int 16
    %0 = torch.prim.ListConstruct %int16, %int784 : (!torch.int, !torch.int) -> !torch.list<int>
    %1 = torch.aten.view %arg2, %0 : !torch.vtensor<[16,28,28],f32>, !torch.list<int> -> !torch.vtensor<[16,784],f32>
    %2 = torch.aten.transpose.int %arg0, %int0, %int1 : !torch.vtensor<[10,784],f32>, !torch.int, !torch.int
                                                     -> !torch.vtensor<[784,10],f32>
    %3 = torch.aten.mm %1, %2 : !torch.vtensor<[16,784],f32>, !torch.vtensor<[784,10],f32> -> !torch.vtensor<[16,10],f32>
    %4 = torch.aten.mul.Scalar %arg1, %int1 : !torch.vtensor<[10],f32>, !torch.int -> !torch.vtensor<[10],f32>
    %5 = torch.aten.add.Tensor %4, %3, %int1 : !torch.vtensor<[10],f32>, !torch.vtensor<[16,10],f32>, !torch.int
                                            -> !torch.vtensor<[16,10],f32>
    %6 = torch.aten.relu %5 : !torch.vtensor<[16,10],f32> -> !torch.vtensor<[16,10],f32>
    return %6, %1, %6 : !torch.vtensor<[16,10],f32>, !torch.vtensor<[16,784],f32>, !torch.vtensor<[16,10],f32>
  }
}
```

LLVM MLIR

MLIR - Dialects

https://github.com/llvm/torch-mlir/blob/main/include/torch-mlir/Dialect/Torch/IR/GeneratedTorchOps.td#L4045

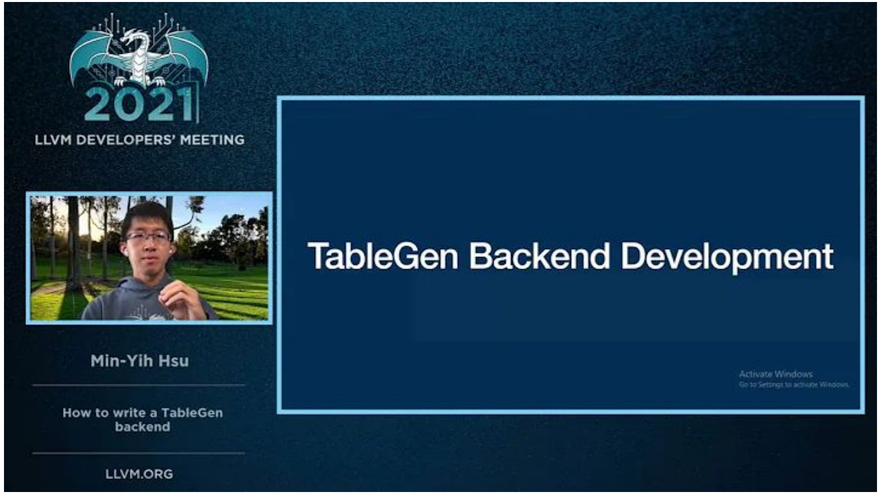
- Dialect Infrastructure
  - Human-readable Text format for SSA Graphs
  - Namespaces for Operations and Types
  - Basics are built-in
  - Boilerplate C++ classes and verifiers can be largely auto-generated from definitions using *TableGen*
- General Graph Transformations
  - Through “Pattern Rewrites”
- Translation between different dialects
  - Called “Conversion” - can be partial
  - E.g. “torch” -> “linalg” -> “LLVM” in theory enables lowering through LLVM IR to any target LLVM has a backend for
    - **In practice WIP!**

```
def Torch_AtenMatmulOp : Torch_Op<"aten.matmul", [
    AllowsTypeRefinement,
    HasValueSemantics,
    ReadOnly
  ]> {
  let summary = "Generated op for
                 `aten::matmul : (Tensor, Tensor) -> (Tensor)`";
  let arguments = (ins
    AnyTorchTensorType:$self,
    AnyTorchTensorType:$other
  );
  let results = (outs
    AnyTorchTensorType:$result
  );
  let hasCustomAssemblyFormat = 1;
  let extraClassDefinition = [{
    ParseResult AtenMatmulOp::parse(OpAsmParser &parser,
                                    OperationState &result) {
      return parseDefaultTorchOp(parser, result, 2, 1);
    }
    void AtenMatmulOp::print(OpAsmPrinter &printer) {
      printDefaultTorchOp(printer, *this, 2, 1);
    }
  }];
}
```

MLIR - Dialects

https://github.com/llvm/torch-mlir/blob/main/include/torch-mlir/Dialect/Torch/IR/GeneratedTorchOps.td#L4045

Watch Min’s TableGen Talk!



2021

LLVM DEVELOPERS’ MEETING

TableGen Backend Development

Min-Yih Hsu

How to write a TableGen backend

LLVM.ORG

https://www.youtube.com/watch?v=UP-LBRbvI_U

```
def Torch_AtenMatmulOp : Torch_Op<"aten.matmul", [
    AllowsTypeRefinement,
    HasValueSemantics,
    ReadOnly
  ]> {
  let summary = "Generated op for
                 `aten::matmul : (Tensor, Tensor) -> (Tensor)`";
  let arguments = (ins
    AnyTorchTensorType:$self,
    AnyTorchTensorType:$other
  );
  let results = (outs
    AnyTorchTensorType:$result
  );
  let hasCustomAssemblyFormat = 1;
  let extraClassDefinition = [{
    ParseResult AtenMatmulOp::parse(OpAsmParser &parser,
                                    OperationState &result) {
      return parseDefaultTorchOp(parser, result, 2, 1);
    }
    void AtenMatmulOp::print(OpAsmPrinter &printer) {
      printDefaultTorchOp(printer, *this, 2, 1);
    }
  }];
}
```

MLIR - Pattern Rewrites

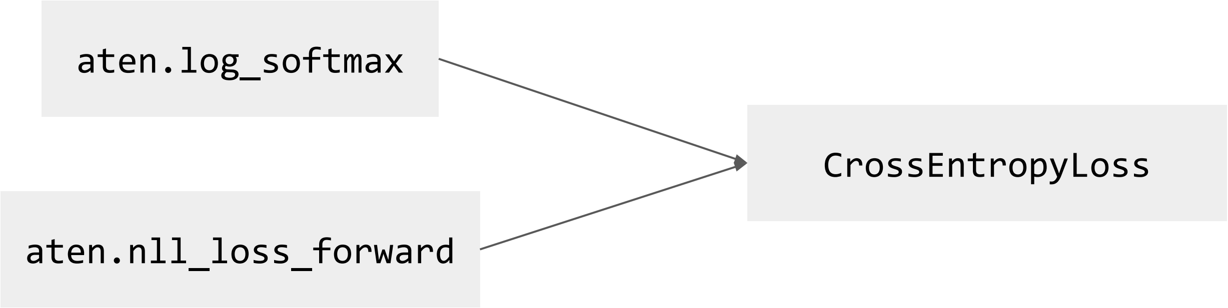
- Generic DAG-to-DAG Transformations
  - Inspired by LLVM's instruction selection algorithm(8)
  - Can be specified declaratively or using C++
- Different algorithms for pattern application ("Drivers")
  - Cost models
  - Bottom-up, Top-Down, Greedy
  - Debugging, Filters, Diagnostics

---

8) https://eli.thegreenplace.net/2013/02/25/a-deeper-look-into-the-llvm-code-generator-part-1

MLIR - Pattern Rewrites

- e.g. `torch.nn.CrossEntropyLoss`(9)



`aten.log_softmax`

`aten.nll_loss_forward`

`CrossEntropyLoss`

---

9) https://pytorch.org/docs/stable/generated/torch.nn.CrossEntropyLoss.html

MLIR - Pattern Rewrites

https://github.com/llvm/torch-mlir/blob/main/lib/Conversion/TorchToLinalg/Pooling.cpp#L128

```cpp
class ConvertAtenMaxPool2dOp : public OpConversionPattern<AtenMaxPool2dOp> {
public:
  using OpConversionPattern::OpConversionPattern;
  LogicalResult
  matchAndRewrite(AtenMaxPool2dOp op, OpAdaptor adaptor,
                  ConversionPatternRewriter &rewriter) const override {
    if (failed(verifyLinalgCompatibleTypes(op, rewriter)))
      return failure();

    TypeConverter *typeConverter = getTypeConverter();
    Value self = adaptor.getSelf();
    int64_t selfRank = self.getType().cast<RankedTensorType>().getRank();
    // TODO: Add support for 3D inputs.
    if (selfRank == 3)
      return rewriter.notifyMatchFailure(
          op, "unimplemented: only support 4D input");

    bool ceilMode;
    SmallVector<Value, 2> kernelSizeIntValues;
    SmallVector<int64_t, 2> strideInts, paddingInts, dilationInts;
    if (!matchPattern(op.getDilation(), m_TorchListOfConstantInts(dilationInts)))
      return rewriter.notifyMatchFailure(op,
                                         "only support constant int dilations");
    if (failed(checkAndGetPoolingParameters<AtenMaxPool2dOp>(
            op, rewriter, typeConverter, ceilMode, kernelSizeIntValues,
            strideInts, paddingInts)))
      return rewriter.notifyMatchFailure(op, "invalid pooling parameters");

    Type elementType =
        self.getType().cast<RankedTensorType>().getElementType();
    auto smallestFPValueAttr = rewriter.getFloatAttr(
        elementType,
        APFloat::getLargest(
            elementType.cast<mlir::FloatType>().getFloatSemantics(),
            /*Negative=*/true));
    SmallVector<Value, 4> outTensorShape;
    // `maxpool2d` contains the result of maxpool2d operation over the input.
    Value maxPool2d, paddedInput;
    if (failed(createPoolingOp<linalg::PoolingNchwMaxOp>(
            op, rewriter, self, /*supportNonFPInput=*/false, ceilMode,
            kernelSizeIntValues, strideInts, paddingInts, dilationInts,
            smallestFPValueAttr, outTensorShape, paddedInput, maxPool2d)))
      return rewriter.notifyMatchFailure(op, "unable to compute maxpool2d");
    Type newResultType = getTypeConverter()->convertType(op.getType());
    rewriter.replaceOpWithNewOp<tensor::CastOp>(op, newResultType,
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    return success();
  }
};
```

MLIR - Pass Infrastructure

https://mlir.llvm.org/docs/PassManagement

- Pass Managers
    - `OperationPass` covers everything: Operation, Block, Region, Function, and Module
- Passes group sets of Transformation Patterns
    - Conversion
        - Dialect A -> Dialect B
        - Convert Types and Operations
        - Full or Partial
        - E.g., “Tensor” -> “MemRef”
    - Canonicalization
        - Dialect A -> Dialect A
        - E.g., “x+x -> x*2”, Fusion, Tiling, etc.
- Analyses
    - No common base class, constructed on the fly
    - Passes must register analysis state invalidation

MLIR - PDL

https://github.com/llvm/llvm-project/blob/main/mlir/test/Rewrite/pdl-bytecode.mlir

- “traditional” Pattern Rewrites in C++
  - But also possible declaratively:

```
def : Pat<
  (AOp $input, ignored_attr),
  (DOp (BOp:$b_result) $b_result)
>;
```

- Generalization: DSL for Pattern Rewrites
  - https://mlir.llvm.org/docs/PDLL/
  - Transform MLIR using MLIR!
  - Dialect “PDL Interp”
  - Has Bytecode definition and Interpreter

```
module @patterns {
  pdl_interp.func @matcher(%root : !pdl.operation) {
    %results = pdl_interp.get_results of %root :
!pdl.range<value>
    %types = pdl_interp.get_value_type of %results :
!pdl.range<type>
    pdl_interp.apply_constraint
"multi_entity_var_constraint"(%results, %types :
!pdl.range<value>, !pdl.range<type>) -> ^pat, ^end

  ^pat:
    pdl_interp.record_match @rewriters::@success(%root :
!pdl.operation) : benefit(1), loc([%root]) -> ^end

  ^end:
    pdl_interp.finalize
  }

  module @rewriters {
    pdl_interp.func @success(%root : !pdl.operation) {
      %op = pdl_interp.create_operation
"test.replaced_by_pattern"
      pdl_interp.erase %root
      pdl_interp.finalize
    }
  }
}
```

But wait! There’s more: 2020 LLVM Developers’ Meeting: M. Amini & R. Riddle “MLIR Tutorial” https://www.youtube.com/watch?v=Y4SvqTtOIDk

Saving FLOPs with Sparsity

Specifically, static activation sparsity in Attention Decoder Masking schemes

Self Attention Decoder Masking

Seminal Transformer Paper

- Originally targeted translation tasks
    - “Encoder” -> source language
    - “Decoder” -> target language
- GPT skips Encoder completely
    - Targets := Inputs[1:]
    - Basis for almost all LLMs today

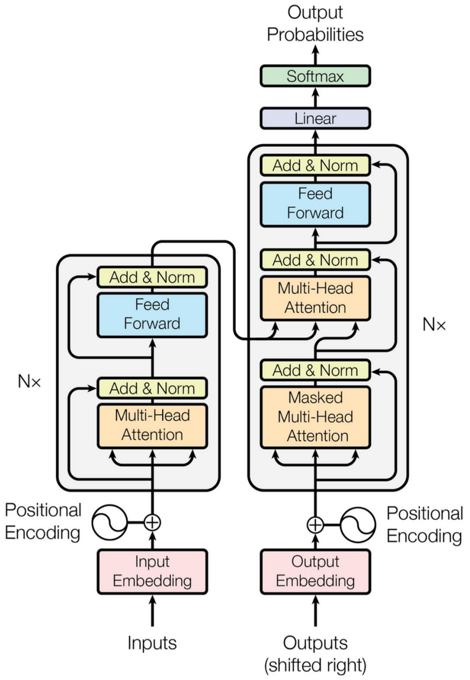


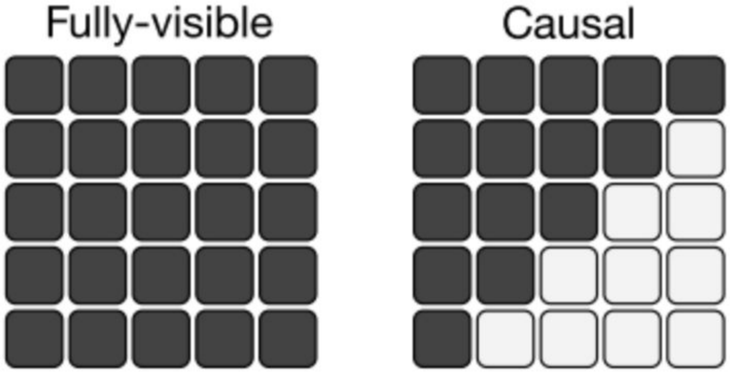
Figure 1: The Transformer - model architecture.

https://arxiv.org/abs/1706.03762

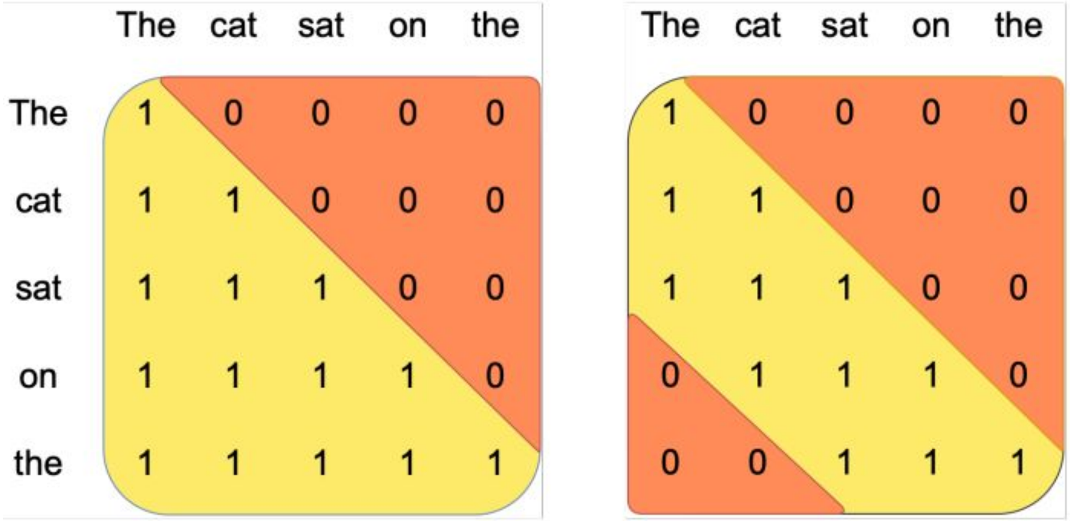
Self Attention Decoder Masking

In Self Attention, masking is typically $O(n^2)$ memory

- N = Sequence Length
  - Typical: 64K, 128K, …
  - A key bottleneck for models today (!)
- On the right hand side you can see a “typical” masking setup
  - white token positions are never used (i.e., they are sparse)
  - With a sequence length of 131072 tokens, this means **8,589,934,592 elements** (half of 131072 squared) are sparse



There are many Attention Decoder Masking Schemes



	The	cat	sat	on	the
The	1	0	0	0	0
cat	1	1	0	0	0
sat	1	1	1	0	0
on	1	1	1	1	0
the	1	1	1	1	1

Vanilla Attention

	The	cat	sat	on	the
The	1	0	0	0	0
cat	1	1	0	0	0
sat	1	1	1	0	0
on	0	1	1	1	0
the	0	0	1	1	1

Sliding Window Attention

https://arxiv.org/abs/2310.06825

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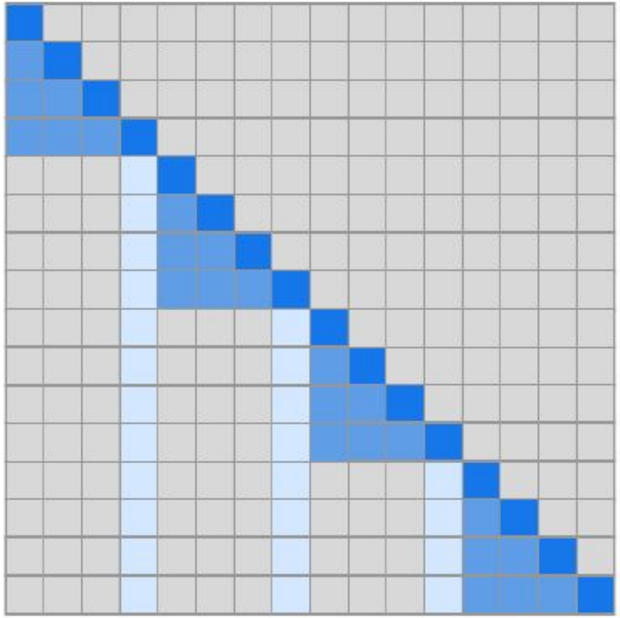


https://arxiv.org/pdf/1904.10509

Main Idea: Avoid Generating Code for Sparse Regions

Two problems:

1. Mask structure is unknown beforehand
2. Mask sparsity should be transitive for downstream elementwise computations, e.g.:

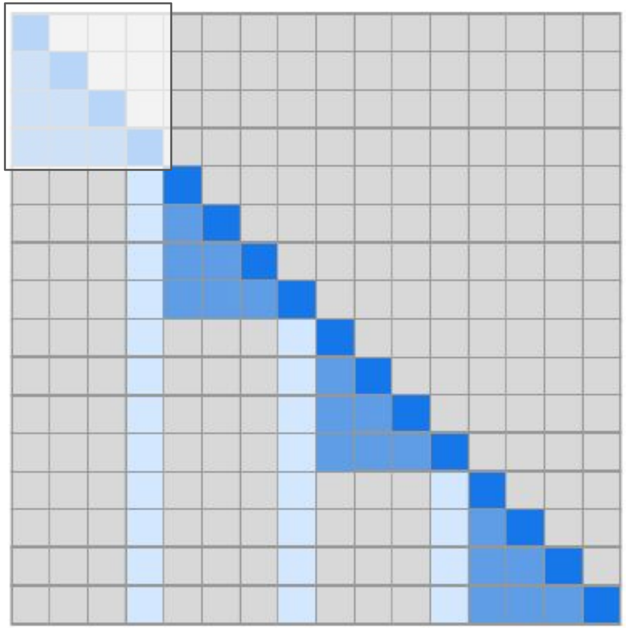
```
out1 = softmax(input * mask)

out2 = out1 * input
```

#1: Mask Structure is Unknown

Instantiate mask tiles to analyze structure during compilation:

- Materialize iteratively in tiles
- Mark each tile as “active” or “inactive”
- e.g.

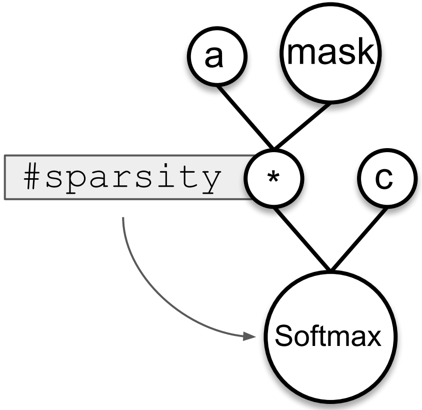
```
#sparsity = {
    [(0,0),(4,4)],
    [(0,4),(4,8)],
    [(4,4),(8,8)],
        ...
```



#2: Mask Sparsity should Transfer Downstream

Assuming we have the sparsity structure in the given format

- Annotate the original instantiation of the mask in the IR
- Propagate that annotation to downstream operations based on defined rules to ensure correctness



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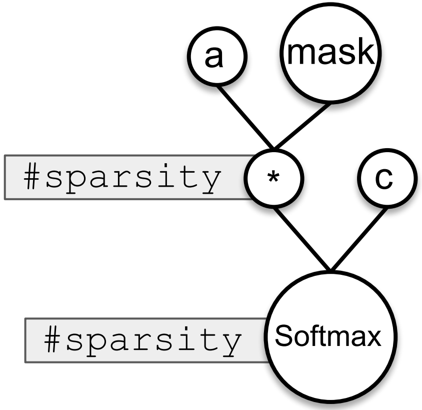

Q&A

Thank you!