### **Naums Mogers**

Aaron Smith, Dimitrios Vytiniotis Michel Steuwer, Christophe Dubach Ryota Tomioka

# Towards Mapping Lift To Deep Neural Networks



EPSRC Centre for Doctoral Training in Pervasive Parallelism



### Convolution

- Many popular NN architectures depend on convolution
  - AlexNet <sup>(2012)</sup>
  - ZFNet<sup>(2013)</sup>
  - GoogleNet<sup>(2014)</sup>
  - VGGNet<sup>(2014)</sup>
  - ResNet<sup>(2015)</sup>

### Runtime of convolution and other layers (VGG measured on Mali GPU with clBLAS)



### **Convolution: algorithms**

### Stencils

Im2col

Fast Fourier transform

### Winograd

### **Convolution: stencils**



### **Convolution:** im2col



#### Input image size in the two methods (1<sup>st</sup> layer of VGG)



### **GEMM in neural networks**

Both stencil and im2col methods for convolution rely heavily on GEMM

GEMM is also the basis of fully connected layers

MLPs make for a large portion of server workloads

### Hardware accelerators



Image source: https://tomshardware.co.uk



**FPGAs** 

Image source: https://eetimes.com



**ASICs** 



Image source: https://blogs.microsoft.com

#### Examples: TPU, BrainWave, DianNao, Huawei Da Vinci, Movidius Myriad

#### All accelerators feature:

Large memory High bandwidth Multidimensional computational units

Multidimensional computational units are exposed in instruction sets:

- $\Box$  VVAdd32, VVAdd64
- □ VVMul32, VVMul64, VVMul128
- □ MVMul32, MVMul64, MVMul128

Finding opportunities to use these primitives is challenging

Using built-in primitives is made harder by:

#### Other optimisations

- Parallelisation
- Tiling (for limited shared memory)
- Memory coalescing
- Prefetching
- *(etc)*

#### Individual device characteristics

#### GEMM

#### GEMM







### Questions:

Data contiguity

Data size

Efficient memory accesses

Data type

### The problem

- Combine device-specific operators optimally
- Design a performance portable approach
- Automate and abstract the process from the user



### Lift: the approach

# 1. Separate algorithm (WHAT) from implementation (HOW)

GEMM

### Lift: the approach

### 2. Detect and rewrite patterns



### Lift in context

### Current landscape



### Lift in context





### Lift in context

### The focus of this talk



### Lift: IR

#### Data types

Int, Float8 / Float16 / Float32, Arrays

#### Algorithmic patterns

Map, Slide, Reduce, Zip, Join, Split

#### Address space operators

toChip, toDram, toOutput

#### Arithmetic operators

- ScalarAdd, VVAdd, MVAdd, MMAdd
- ScalarMul, VVMul, MVMul, MMMul
- VVRelu, VVTanh

### Lift: example rewrite rules



#### Rewrite rule system

- Generic and customisable
- 3 levels: DSL, algorithmic, hardware
- Extensible

### A fully connected layer

```
1 for (int i = 0; i < n_neurons; i++) {
2  for (int j = 0; j < x_length; j++) {
3    temp[j + x_length*i] =
4         X[j] * W[j + x_length*i];
5    }
6
7  OUT[i] = B[i];
8  for (int j = 0; j < x_length; j++) {
9    OUT[j] += temp[j + x_length*i];
10    }
11 }</pre>
```



1 temp = MVMul(W, X); 2 OUT = VVAdd(temp, B);



2 W,

3 B) >>

- 4 Map((neuronW, neuronB) =>
- 5 VVMul(neuronW, toChip(X)) >>
- 6 Reduce(ScalarAdd, neuronB)) >>
- 7 VVRelu() >> toOutput()

#### Ŧ

#### 1 Zip(

- 2 W,
- 3 B) >>
- 4 Map((neuronW, neuronB) =>
- 5 VVMul(neuronW, toChip(X)) >>
- 6 Reduce(ScalarAdd, neuronB)) >>
- 7 VVRelu() >> toOutput()

// GEMV rewrite
matrix >> Map(row =>
 VVMul(row, vector) >>
 Reduce(ScalarAdd, 0))
 I I I
MVMul(matrix, vector)

#### 1 Zip(

- 2 W,
- 3 B) >>
- 4 Map((neuronW, neuronB) =>
- 5 VVMul(neuronW, toChip(X)) >>
- 6 Reduce(ScalarAdd, neuronB); >>
- 7 VVRelu() >> toOutput()

#### <Extract Initializer From Reduce>



12 }

1 Zip(

2 W,

3 B) >>

4 Map((neuronW, neuronB) =>

- 5 VVMul(neuronW, toChip(X)) >>
- 6 Reduce(ScalarAdd, 0) >>
- 7 ScalarAdd(neuronB)) >>

```
8 VVRelu() >> toOutput()
```

```
1 for (int i = 0; i < n_neurons; i++) {
2  for (int j = 0; j < x_length; j++) {
3    temp[j + x_length*i] =
4         X[j] * W[j + x_length*i];
5    }
6
7  OUT[i] = 0;
8  for (int j = 0; j < x_length; j++) {
9      OUT[j] += temp[j + x_length*i];
10    }
11  OUT[i] += B[i];
12 }</pre>
```



```
1 for (int i = 0; i < n_neurons; i++) {
2  for (int j = 0; j < x_length; j++) {
3    temp[j + x_length*i] =
4         X[j] * W[j + x_length*i];
5    }
6
7  OUT[i] = 0;
8  for (int j = 0; j < x_length; j++) {
9      OUT[j] += temp[j + x_length*i];
10    }
11  OUT[i] += B[i];
12 }</pre>
```

<Map fission>





```
1 for (int i = 0; i < n_neurons; i++) {
    for (int j = 0; j < x_length; j++) {</pre>
    temp[j + x_length*i] =
        X[j] * W[j + x_length*i];
    }
6 }
7 for (int i = 0; i < n_neurons; i++) {</pre>
     OUT[i] = 0;
    for (int j = 0; j < x_length; j++) {</pre>
       OUT[j] += temp[j + x_length*i];
10
     }
11
12
    OUT[i] += B[i];
13 }
```



```
1 for (int i = 0; i < n_neurons; i++) {
    for (int j = 0; j < x_length; j++) {</pre>
    temp[j + x_length*i] =
        X[i] * W[i + x_length*i];
    }
6 }
7 for (int i = 0; i < n_neurons; i++) {</pre>
     OUT[i] = 0;
    for (int j = 0; j < x_length; j++) {</pre>
       OUT[j] += temp[j + x_length*i];
10
     }
11
12
     OUT[i] += B[i];
13 }
```

<A couple rewrites later...>





```
1 for (int i = 0; i < n_neurons; i++) {
2  for (int j = 0; j < x_length; j++) {
3    temp[j + x_length*i] =
4         X[j] * W[j + x_length*i];
5    }
6    OUT[i] = 0;
7    for (int j = 0; j < x_length; j++) {
8        OUT[j] += temp[j + x_length*i];
9    }
10 }
11 for (int i = 0; i < n_neurons; i++) {
12    OUT[i] += B[i];
13 }</pre>
```



```
1 for (int i = 0; i < n_neurons; i++) {
2   for (int j = 0; j < x_length; j++) {
3     temp[j + x_length*i] =
4         X[j] * W[j + x_length*i];
5   }
6   OUT[i] = 0;
7   for (int j = 0; j < x_length; j++) {
8       OUT[j] += temp[j + x_length*i];
9   }
10 }
11 for (int i = 0; i < n_neurons; i++) {
12   OUT[i] += B[i];
13 }</pre>
```



```
1 Zip(
2 MVMul(W, X >> toChip)
3 B) >>
4 Map((neuronWXreduced, neuronB) =>
5 neuronWXreduced >>
6 ScalarAdd(neuronB)) >>
7 VVRelu() >> toOutput()
```

```
1 temp = MVMul(W, X);
2 for (int i = 0; i < n_neurons; i++) {
3     OUT[i] += B[i];
4 }</pre>
```

![](_page_35_Figure_1.jpeg)

```
1 temp = MVMul(W, X);
2 for (int i = 0; i < n_neurons; i++) {
3     OUT[i] += B[i];
4 }</pre>
```

< Vectorise Map-Zip >

![](_page_36_Figure_1.jpeg)

![](_page_36_Figure_2.jpeg)

1 temp = MVMul(W, X);
2 for (int i = 0; i < n\_neurons; i++) {
3 OUT[i] += B[i];
4 }</pre>

1 temp = MVMul(W, X);
2 OUT = VVAdd(temp, B);

1 VVAdd(
2 MVMul(W, X >> toChip)
3 B) >>
4 VVRelu() >> toOutput()

1 temp = MVMul(W, X); 2 OUT = VVAdd(temp, B);

### **Preliminary results**

Functional correctness on the BrainWave accelerator

Performance measurements on Mali GPU

Average runtime of conv layers in VGG

![](_page_38_Figure_4.jpeg)

### **Future work**

Generation of both OpenCL kernel and host runtime

Performance evaluation on popular DNN architectures

Support for more hardware accelerators