# Spatial: A Language and Compiler for Application Accelerators

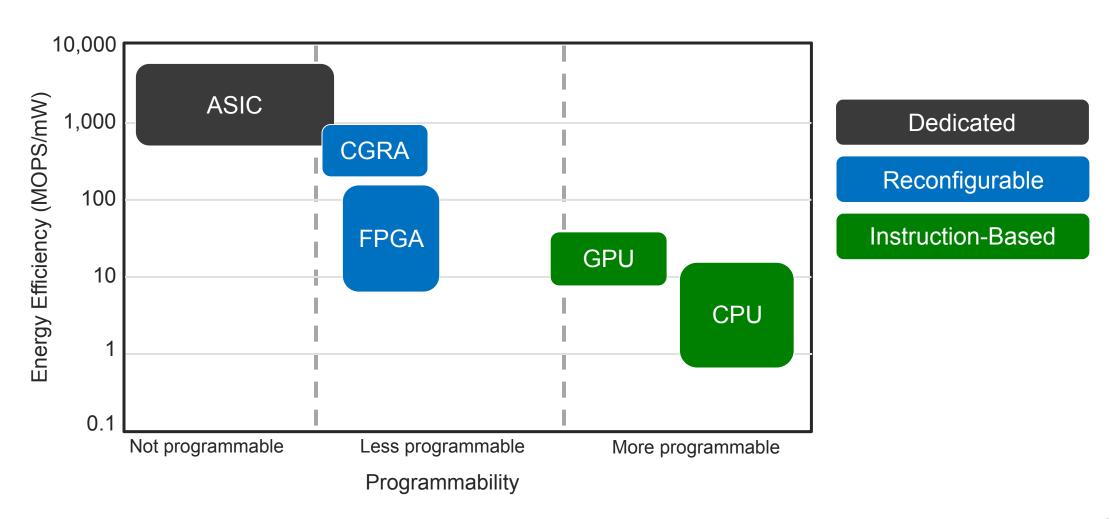
Raghu Prabhakar
Stanford University / SambaNova
Systems

The Market

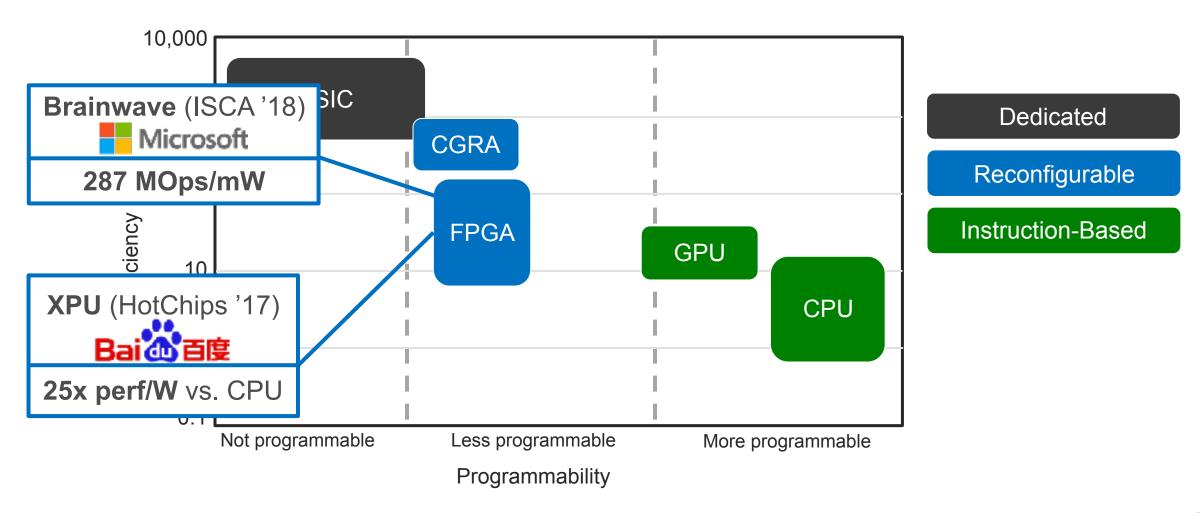
TVM Conference Dec 13, 2018



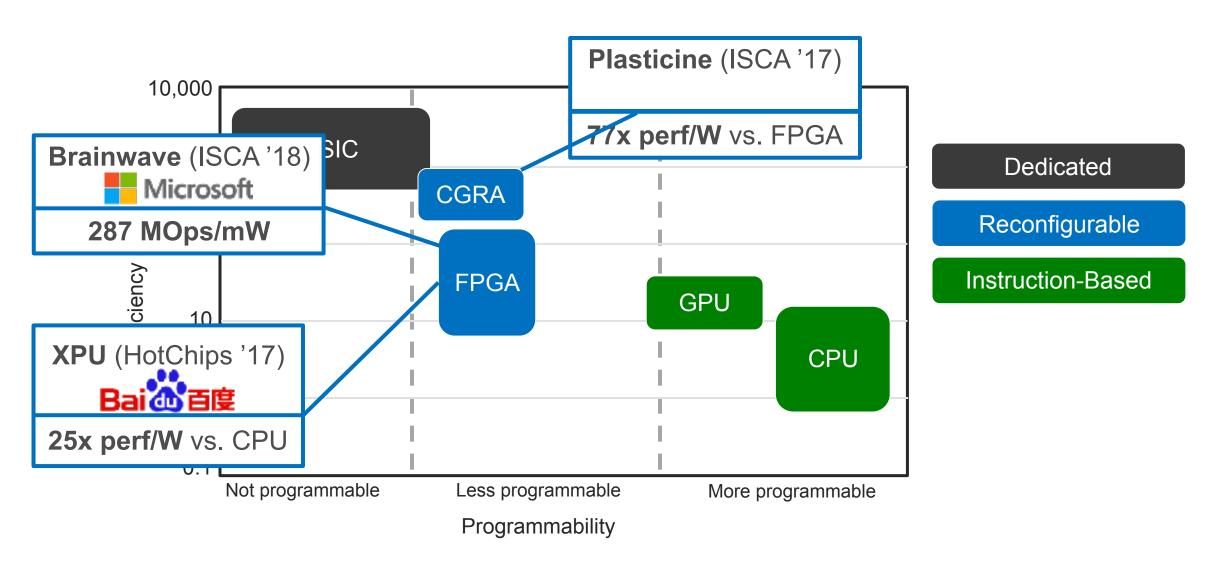
#### The Future Is (Probably) Reconfigurable



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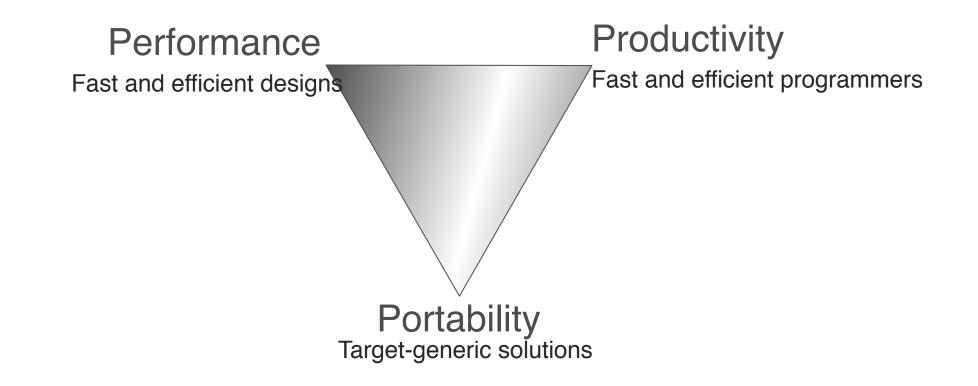


#### **Key Question**

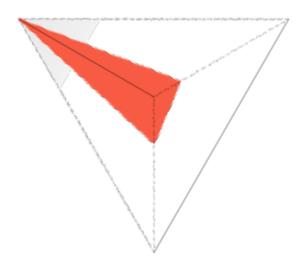
How can we more productively target reconfigurable architectures like FPGAs?

#### **Key Question**

# How can we more productively target reconfigurable architectures like FPGAs?



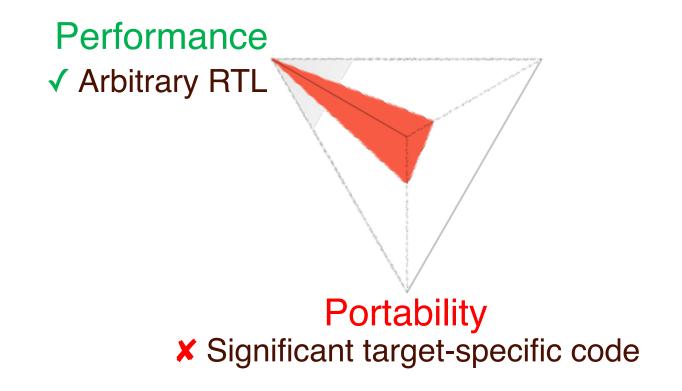
#### Hardware Description Languages (HDLs)



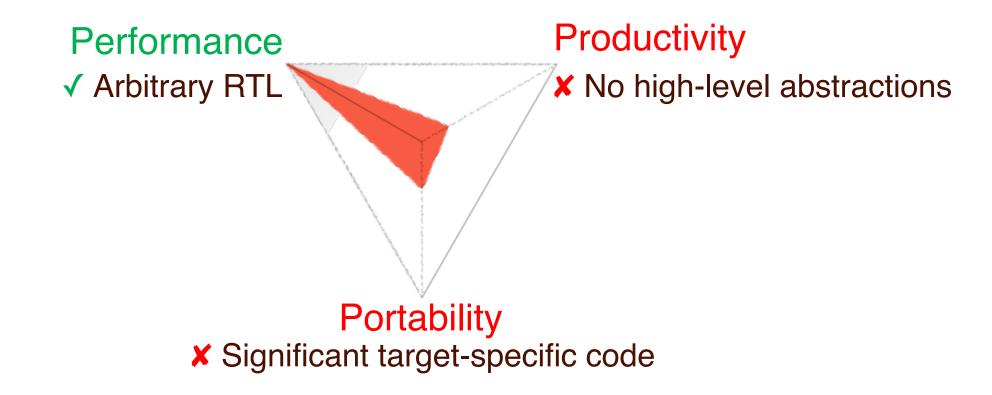
#### Hardware Description Languages (HDLs)



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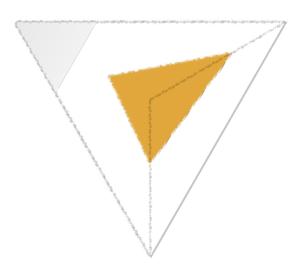


#### Hardware Description Languages (HDLs)



Existing High Level Synthesis (C + Pragmas)

e.g. Vivado HLS, SDAccel, Altera OpenCL



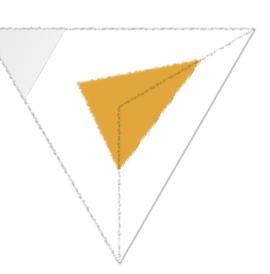
HDLs

#### Existing High Level Synthesis (C + Pragmas)

e.g. Vivado HLS, SDAccel, Altera OpenCL

#### Performance

- No memory hierarchy
- No arbitrary pipelining



HDLs

Existing High Level Synthesis (C + Pragmas)

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No memory hierarchy

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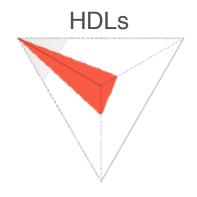
✓ Portable for single vendor

HDLs

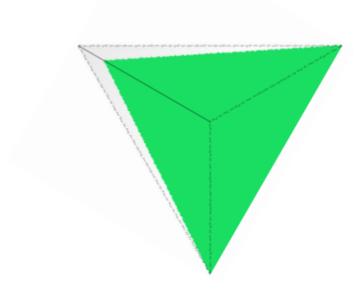
Existing High Level Synthesis (C + Pragmas)

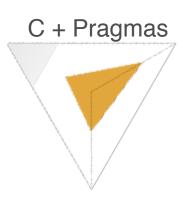
e.g. Vivado HLS, SDAccel, Altera OpenCL

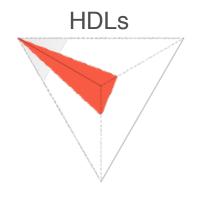
# Performance X No memory hierarchy X No arbitrary pipelining Portability ✓ Portable for single vendor



#### Improved HLS





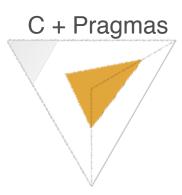


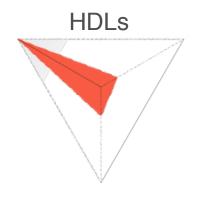
#### Improved HLS



- Memory hierarchy
- √ Arbitrary pipelining







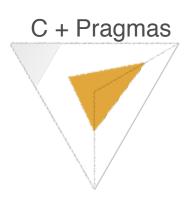
#### Improved HLS

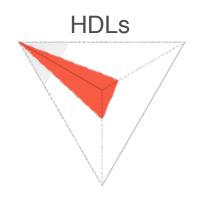


- Memory hierarchy
- √ Arbitrary pipelining

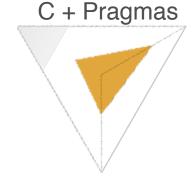


√ Target-generic source across reconfigurable architectures





#### Improved HLS



#### Performance

- Memory hierarchy
- √ Arbitrary pipelining

#### **Productivity**

- ✓ Nested loops
- ✓ Automatic memory banking/buffering
- ✓ Implicit design parameters (unrolling, banking, etc.)
- ✓ Automated design tuning

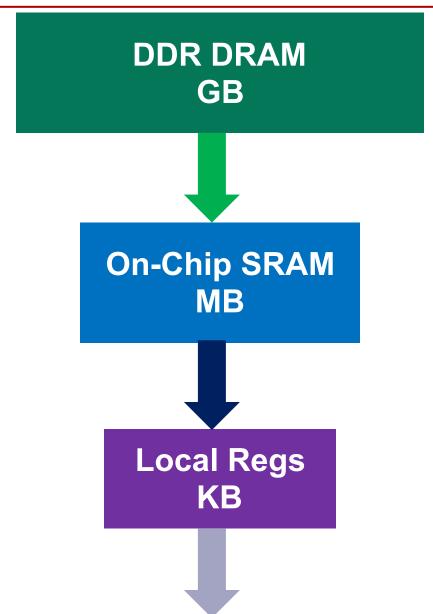
✓ Target-generic source across reconfigurable architectures

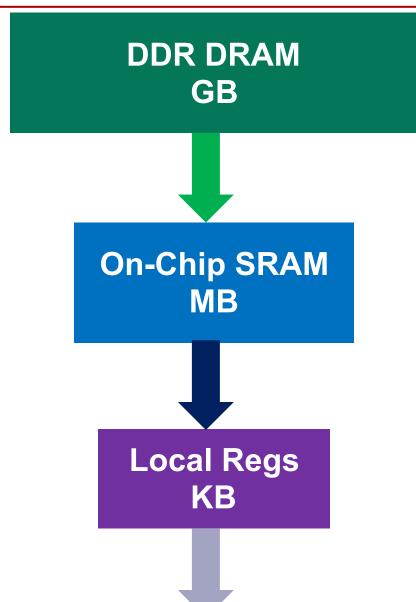
**Portability** 

#### **Introducing Spatial**

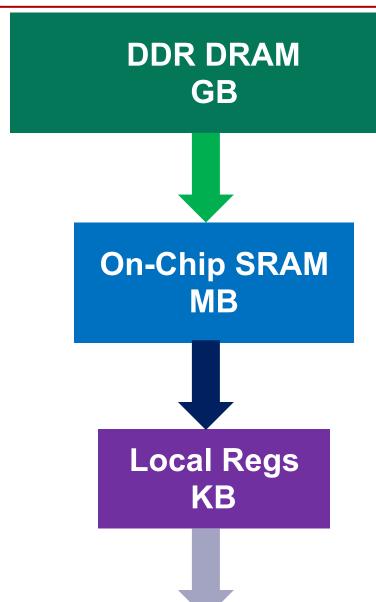


- Programming language to simplify configurable accelerator design
  - Constructs to express:
    - Hierarchical parallel and pipelined data paths
    - explicit memory hierarchies
  - Simple APIs to manage CPU Accelerator communication
- Open source: <a href="https://spatial-lang.org/">https://spatial-lang.org/</a>
- Allows programmers to focus on "interesting stuff"
  - Designed for performance oriented programmers
  - More intuitive than CUDA: dataflow instead of threads



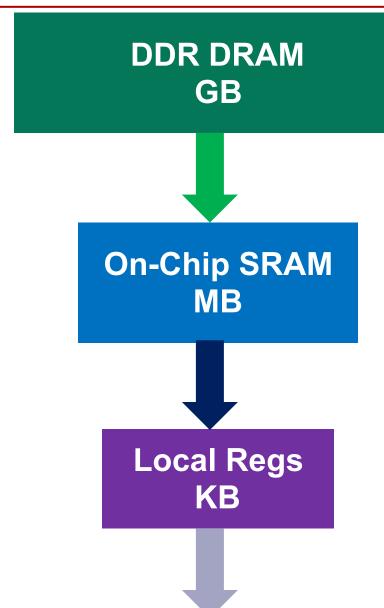


```
val image = DRAM[UInt8]
(H,W)
```



```
val image = DRAM[UInt8]
(H,W)
```

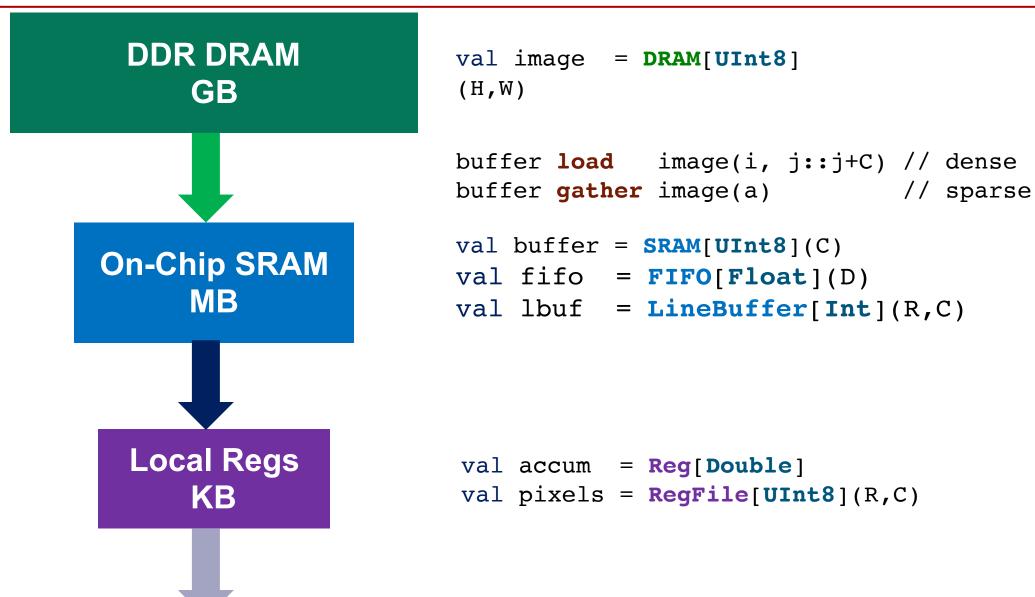
```
val buffer = SRAM[UInt8](C)
val fifo = FIFO[Float](D)
val lbuf = LineBuffer[Int](R,C)
```



```
val image = DRAM[UInt8]
(H,W)

buffer load image(i, j::j+C) // dense
buffer gather image(a) // sparse

val buffer = SRAM[UInt8](C)
val fifo = FIFO[Float](D)
val lbuf = LineBuffer[Int](R,C)
```



Implicit/Explicit parallelization factors (optional, but can be explicitly declared)

```
val P = 16 (1 → 32)
Reduce(0)(N by 1 par P){i =>
  data(i)
}{(a,b) => a + b}
```

## Implicit/Explicit parallelization factors (optional, but can be explicitly declared)

#### Implicit/Explicit control schemes

(also optional, but can be used to override compiler)

```
val P = 16 (1 → 32)
Reduce(0)(N by 1 par P){i =>
   data(i)
}{(a,b) => a + b}
Stream.Foreach(0 until N){i =>
   ...
}
```

Implicit/Explicit parallelization factors (optional, but can be explicitly declared)

#### Implicit/Explicit control schemes

(also optional, but can be used to override compiler)

## **Explicit** size parameters for loop step size and buffer sizes

(informs compiler it can tune this value)

```
val P = 16 (1 \rightarrow 32)
Reduce(0)(N by 1 par P){i =>
  data(i)
\{(a,b) => a + b\}
Stream.Foreach(0 until N){i =>
val B = 64 (64 \rightarrow 1024)
val buffer = SRAM[Float](B)
Foreach(N by B){i =>
```

Implicit/Explicit parallelization factors (optional, but can be explicitly declared)

## Implicit/Explicit control schemes (also optional, but can be used to override compiler)

**Explicit** size parameters for loop step size and buffer sizes (informs compiler it can tune this value)

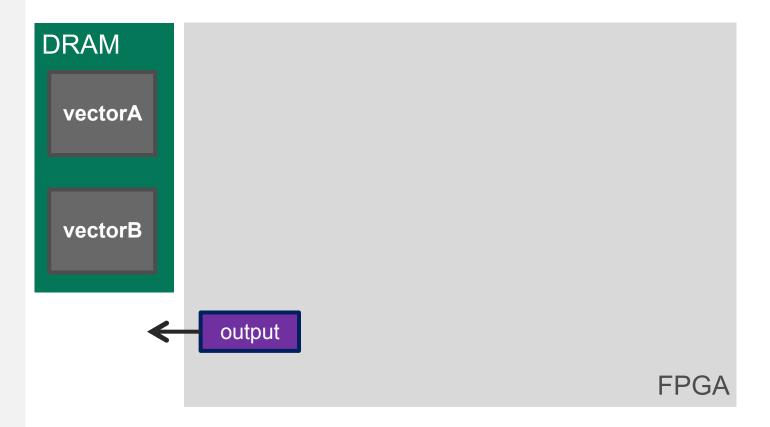
Implicit memory banking and buffering schemes for parallelized access

```
val P = 16 (1 \rightarrow 32)
Reduce(0)(N by 1 par P){i =>
  data(i)
\{(a,b) => a + b\}
Stream.Foreach(0 until N){i =>
val B = 64 (64 \rightarrow 1024)
val buffer = SRAM[Float](B)
Foreach(N by B){i =>
Foreach(64 par 16){i =>
```

```
buffer(i) // Parallel read
}
```

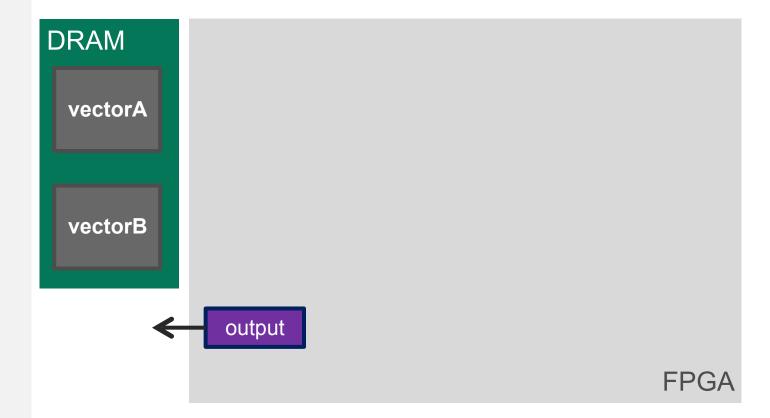
```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
```

Off-chip memory declarations



```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
Accel {
```

Explicit work division in IR



vectorA

vectorB

output

```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
                                DRAM
Accel {
  Reduce(output)(N by B){ i =>
```

Tiled reduction (outer)

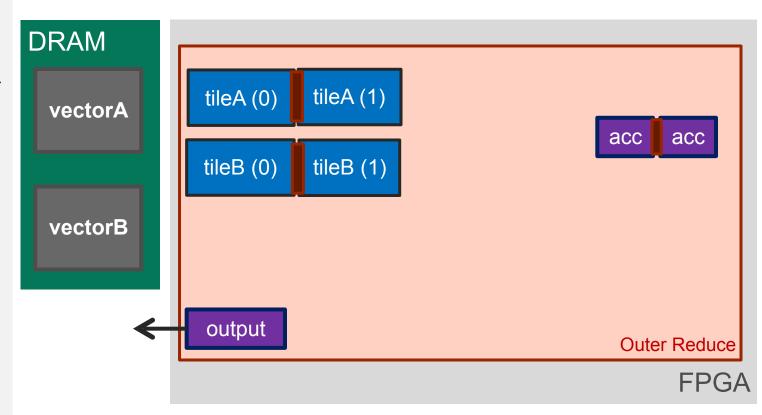
**FPGA** 

Outer Reduce

```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)

Accel {
    Reduce(output)(N by B){ i => val tileA = SRAM[Float](B) val tileB = SRAM[Float](B) val acc = Reg[Float]
```

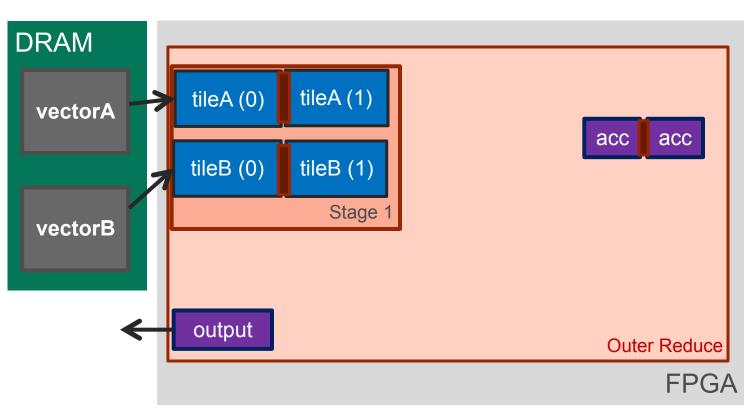
On-chip memory declarations



```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
Accel {
  Reduce(output)(N by B){ i =>
    val tileA = SRAM[Float](B)
    val tileB = SRAM[Float](B)
    val acc = Reg[Float]
    tileA load vectorA(i ::
i+B)
    tileB load vectorB(i ::
i+B)
```

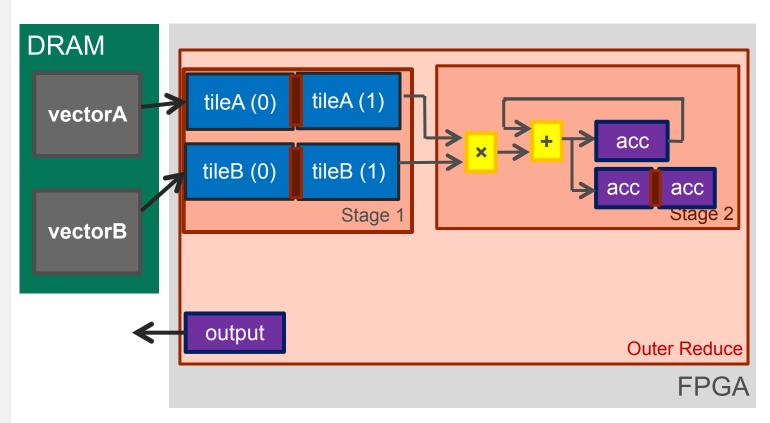
```
DRAM → SRAM transfers

(also have store, scatter, and gather)
```



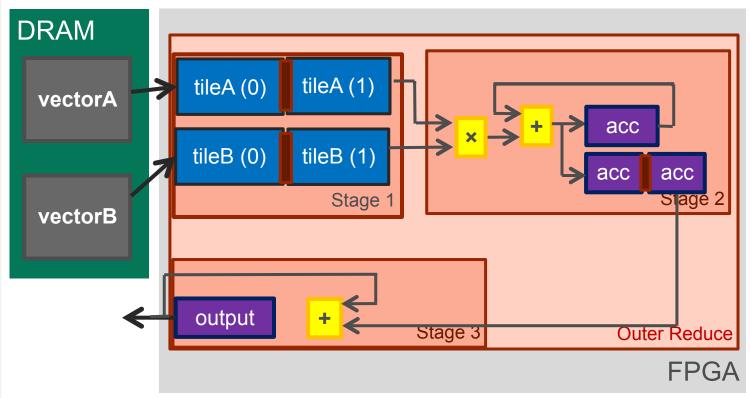
```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
Accel {
  Reduce(output)(N by B){ i =>
    val tileA = SRAM[Float](B)
    val tileB = SRAM[Float](B)
   val acc = Reg[Float]
    tileA load vectorA(i ::
i+B)
    tileB load vectorB(i ::
i+B)
    Reduce(acc)(B by 1){ j =>
      tileA(j) * tileB(j)
    \{a, b => a + b\}
```

Tiled reduction (pipelined)



```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
Accel {
 Reduce(output)(N by B){ i =>
    val tileA = SRAM[Float](B)
   val tileB = SRAM[Float](B)
   val acc = Reg[Float]
    tileA load vectorA(i ::
i+B)
   tileB load vectorB(i ::
i+B)
    Reduce(acc)(B by 1){ j =>
     tileA(j) * tileB(j)
    \{a, b => a + b\}
```

Outer reduce function



### **Dot Product in Spatial**

```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
                                                        Banking strategy
val vectorB = DRAM[Float](N)
                                       Tile Size (B)
                                                                  Parallelism factor #3
                                   DRAM
Accel {
  Reduce(output)(N by B){ i =>
                                               tileA (0)
                                                       tileA (1)
                                     vectorA
    val tileA = SRAM[Float](B)
                                                                            acc
    val tileB = SRAM[Float](B)
                                               tileB (0)
                                                       tileB (1)
    val acc = Reg[Float]
                                                                           acc
                                                                                acc
                                                                                Stage
                                                         Stage
                                    vectorB
    tileA load vectorA(i ::
i+B)
    tileB load vectorB(i ::
                                  Parallelism
                                               output
i+B)
                                                               Stage 3
                                                                             Outer Reduce
                                   factor #2
                                                                                 FPGA
    Reduce (acc) (B by 1) { j =>
                                                       Parallelism factor #1
      tileA(j) * tileB(j)
                                                       Metapipelining toggle
    \{a, b => a + b\}
                                                                                  24
```

### **Dot Product in Spatial**

```
val output = ArgOut[Float]
val vectorA = DRAM[Float](N)
val vectorB = DRAM[Float](N)
Accel {
  Reduce(output)(N by B){ i =>
    val tileA = SRAM[Float](B)
    val tileB = SRAM[Float](B)
    val acc = Reg[Float]
    tileA load vectorA(i ::
i+B)
    tileB load vectorB(i ::
i+B)
    Reduce (acc) (B by 1) { j =>
      tileA(j) * tileB(j)
    \{a, b => a + b\}
  \{a, b => a + b\}
```

# **Dot Product in Spatial**

Spatial Program Design Parameters

# **The Spatial Compiler**

**Spatial Program** 

# **The Spatial Compiler**

**Spatial IR** 

### **The Spatial Compiler**

**Spatial IR** 

Design Parameters

**Control Inference** 

**Control Scheduling** 

**Access Pattern Analysis** 

Mem. Banking/ Buffering

**Area/Runtime Analysis** 

[Optional] Design
Tuning

**Pipeline Unrolling** 

**Pipeline Retiming** 

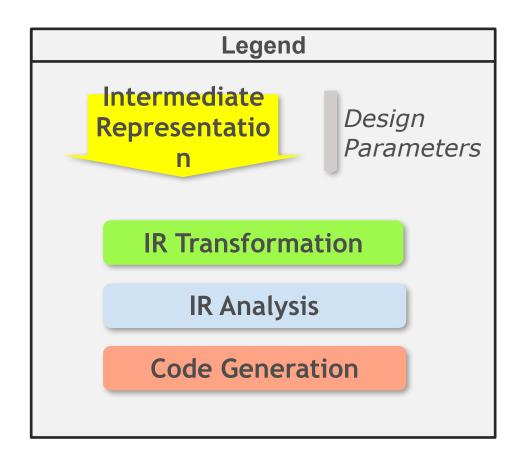
Host Resource
Allocation

**Control Signal** 

Inference

Chisel Code

Generation



### **Control Scheduling**

Spatial IR

**Control Inference** 

#### **Control Scheduling**

Access Pattern Analysis

Mem. Banking/
Buffering

Area/Runtime Analysis
[Optional] Design
Tuning

**Pipeline Unrolling** 

Pipeline Retiming

Host Resource
Allocation
Control Signal

Inference Chisel Code Generation

- Creates loop pipeline schedules
  - Detects data dependencies across loop intervals
  - Calculate initiation interval of pipelines
  - Set maximum depth of buffers
- Supports arbitrarily nested pipelines

(Commercial HLS tools don't support this)

**Spatial IR** 

Design Parameters

**Control Inference** 

**Control Scheduling** 

**Access Pattern Analysis** 

Mem. Banking/ Buffering

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[Optional] Design
Tuning

Pipeline Unrolling

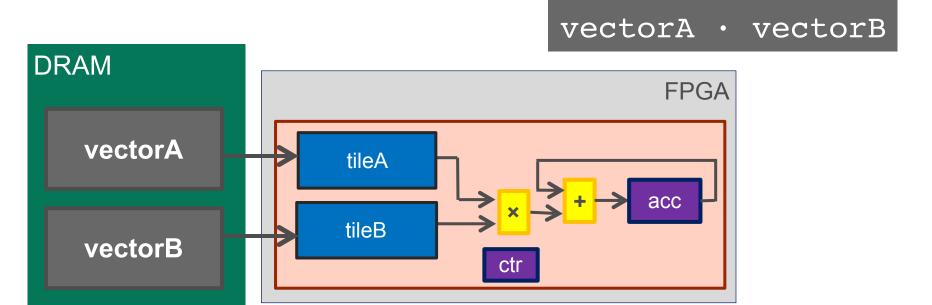
Pipeline Retiming

**Host Resource** 

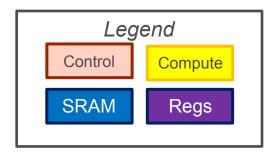
Allocation

Inference Chisel Code Modified Parameters

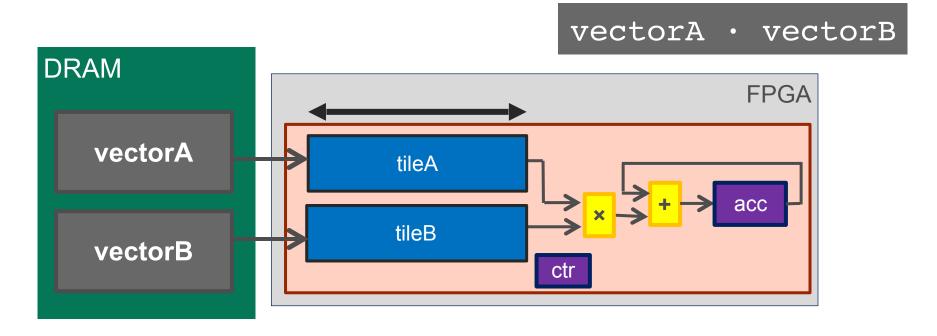
### **Design Space Parameters Example**



Small and simple, but slow!



### **Important Parameters: Buffer Sizes**

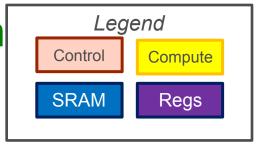


- Increases length of DRAM access
- Increases exploited locality
- Increases local memory sizes

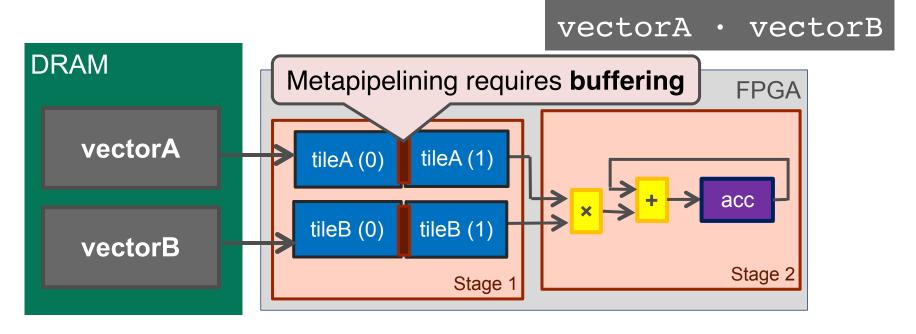
#### Runtime

**Runtim** 

Area



# **Important Parameters: Pipelining**

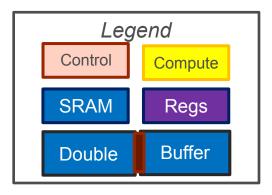


- Overlaps memory and comput
- Increases local memory sizes
- Adds synchronization logic

Runtime

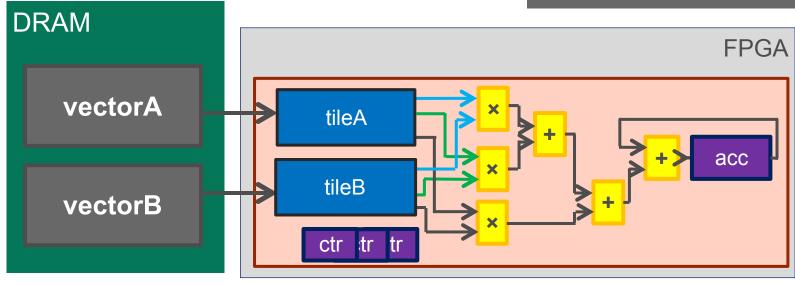
Area

Area

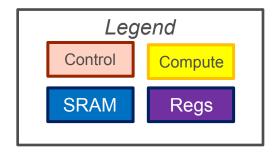


### **Important Parameters: Parallelization**

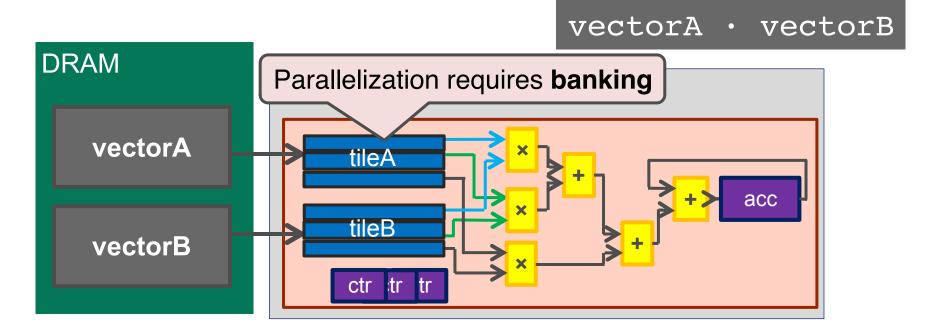
vectorA · vectorB



- Improves element throughput
   Runtime
- Duplicates compute resource Area



### **Important Parameters: Memory Banking**



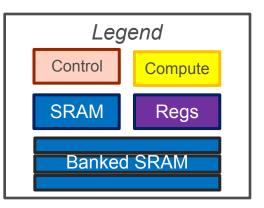
Improves memory bandwidth



Runtime

May duplicate memory resource

Area



**Spatial IR** 

Design Parameters

**Control Inference** 

**Control Scheduling** 

**Access Pattern Analysis** 

Mem. Banking/ Buffering

**Area/Runtime Analysis** 

[Optional] Design
Tuning

Pipeline Unrolling

Pipeline Retiming

**Host Resource** 

Allocation

Inference Chisel Code Modified Parameters

Spatial IR

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Mem. Banking/ Buffering

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[Optional] Design

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Pipeline Retiming

Host Resource
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Control Signal

Inference Chisel Code Modified Parameters

### Original tuning methods:

- Pre-prune space using simple heuristics
- Randomly sample ~100,000 design points
- Model area/runtime of each point

Design Parameters

**Control Inference** 

**Control Scheduling** 

**Access Pattern Analysis** 

Mem. Banking/ Buffering

Area/Runtime Analysis

[Optional] Design

Pipeline Unrolling

Pipeline Retiming

Host Resource

Allocation
Control Signal

Inference Chisel Code Generation Modified Parameters

### Original tuning methods:

- Pre-prune space using simple heuristics
- Randomly sample ~100,000 design points
- Model area/runtime of each point

### Proposed tuning method

Design Parameters

**Control Inference** 

**Control Scheduling** 

**Access Pattern Analysis** 

Mem. Banking/ Buffering

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[Optional] Design

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### Proposed tuning method

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Inference Chisel Code Generation Modified Parameters

### Original tuning methods:

- Pre-prune space using simple heuristics
- Randomly sample ~100,000 design points
- Model area/runtime of each point

### Proposed tuning method

# **The Spatial Compiler: The Rest**

Spatial IR

Control Inference

**Control Scheduling** 

Access Pattern Analysis

Mem. Banking/

Area/Runtime Analysis

[Optional] Design

Tuning

Pipeline Unrolling

Pipeline Retiming

**Host Resource** 

Allocation

**Control Signal** 

Inference

Chisel Code Generation

### Code generation

- Synthesizable Chisel
- C++ code for host CPU

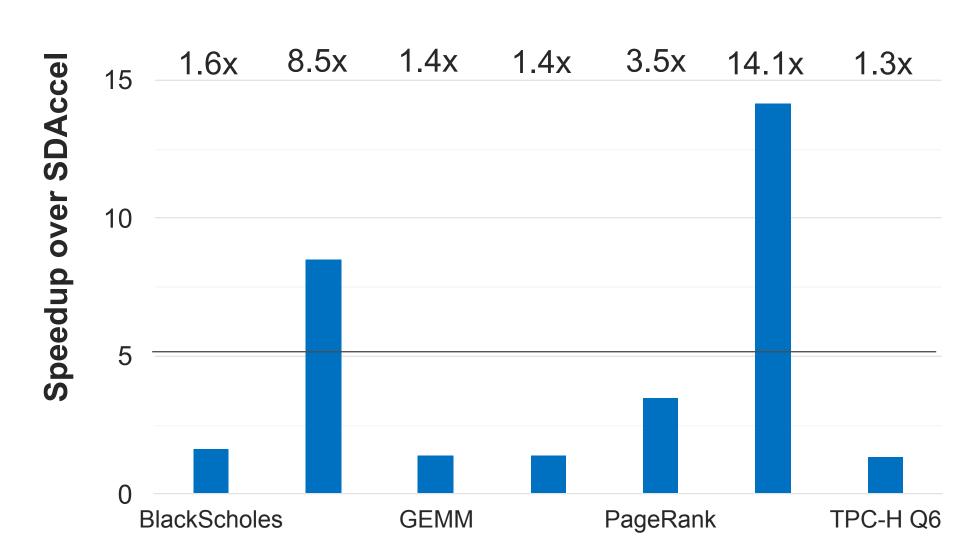
### **Evaluation: Performance**

- FPGA:
  - Amazon EC2 F1 Instance: Xilinx VU9P FPGA
  - Fixed clock rate of 150 MHz
- Applications
  - SDAccel: Hand optimized, tuned implementations
  - Spatial: Hand written, automatically tuned implementations

Execution time = FPGA execution time

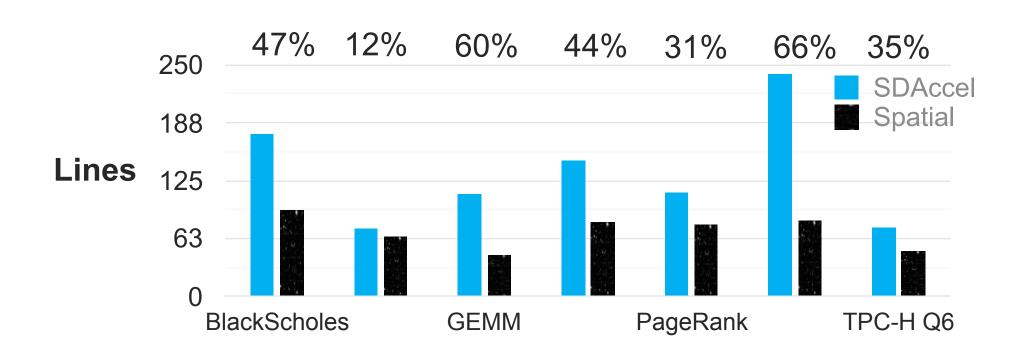
# Performance (Spatial vs. SDAccel)

#### Average 2.9x faster hardware than SDAccel



### **Productivity: Lines of Code**

#### Average 42% shorter programs versus SDAccel

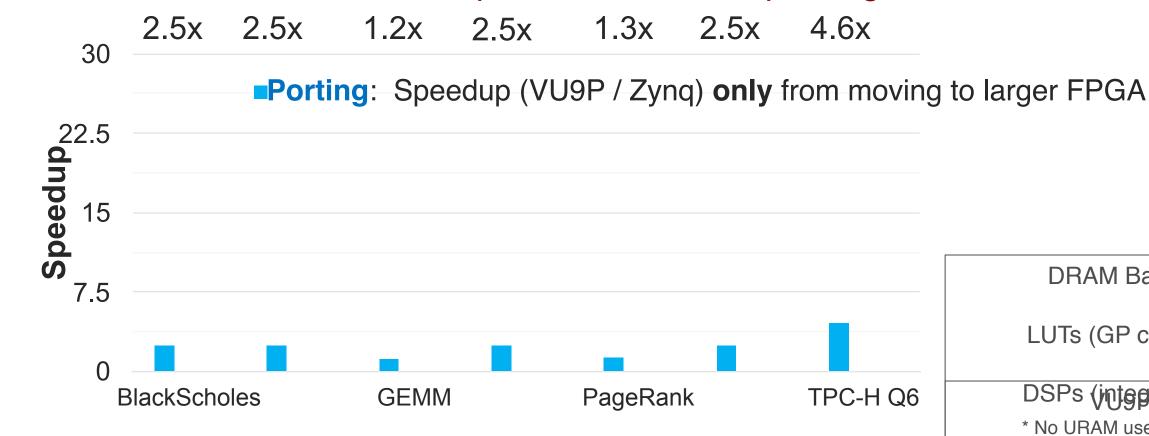


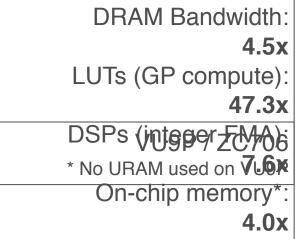
# **Evaluation: Portability**

- FPGA 1
  - Amazon EC2 F1 Instance: Xilinx VU9P FPGA
  - 19.2 GB/s DRAM bandwidth (single channel)
- FPGA 2
  - Xilinx Zynq ZC706
  - 4.3 GB/s
- Applications
  - Spatial: Hand written, automatically tuned implementations
  - Fixed clock rate of 150 MHz

### Portability: VU9P vs. Zynq ZC706

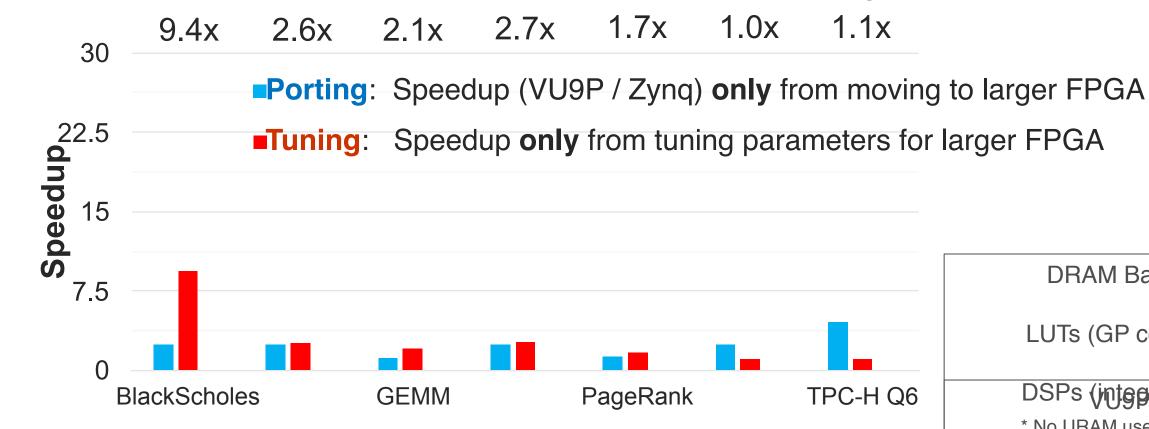
#### Identical Spatial source, multiple targets

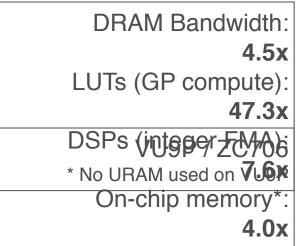




### Portability: VU9P vs. Zynq ZC706

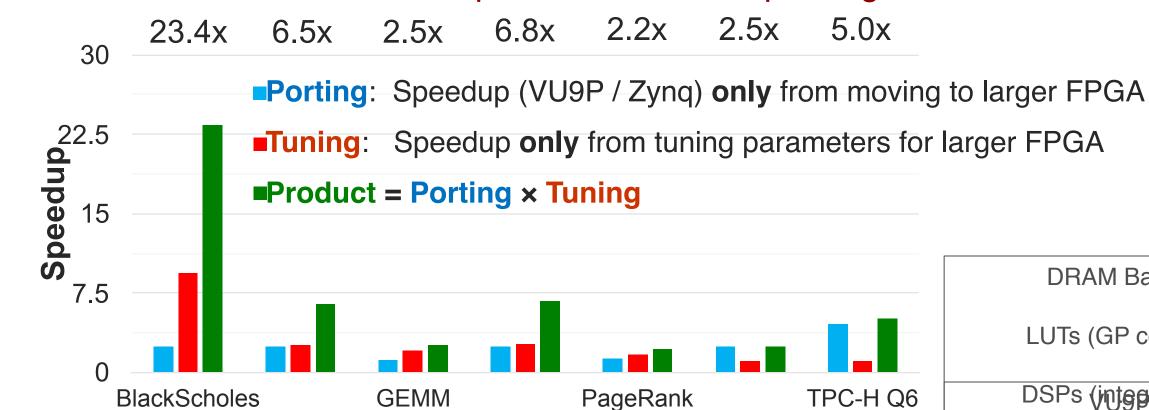
#### Identical Spatial source, multiple targets

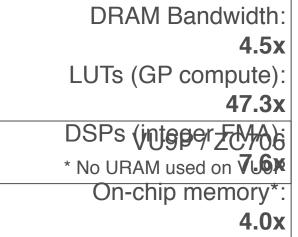




### Portability: VU9P vs. Zynq ZC706

#### Identical Spatial source, multiple targets





### **Portability: Plasticine CGRA**

#### Identical Spatial source, multiple targets Even reconfigurable hardware that isn't an FPGA!

Benchmark	DRAM Band Load	dwidth (%) Store	Resource PCU	e Utilizatio PMU	on (%) AG	<b>Speedup</b> vs. VU9P
BlackScholes	77.4	12.9	73.4	10.9	20.6	1.6
GDA	24.0	0.2	95.3	73.4	38.2	9.8
GEMM	20.5	2.1	96.8	64.1	11.7	55.0
K-Means	8.0	0.4	89.1	57.8	17.6	6.3
TPC-H Q6	97.2	0.0	29.7	37.5	70.6	1.6

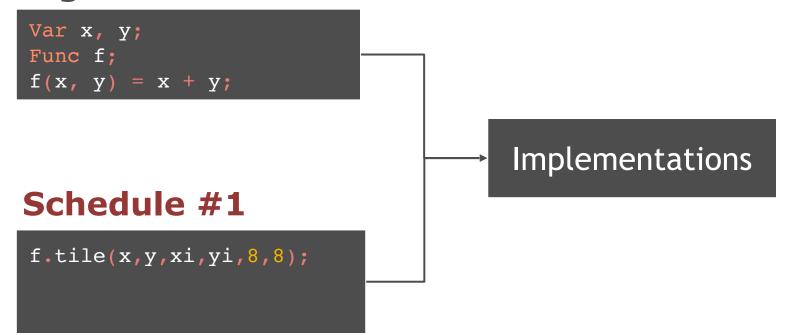
Prabhakar et al. Plasticine: A Reconfigurable Architecture For Parallel Patterns (ISCA '17)

# Halide to Spatial

### What is Halide?

- DSL for computational photography
- Separation between algorithm (what to compute) and schedule (how to compute)
- Straightforward to express and iterate over various schedules

#### **Algorithm**



### What is Halide?

- DSL for computational photography
- Separation between algorithm (what to compute) and schedule (how to compute)
- Straightforward to express and iterate over various schedules

#### **Algorithm**

```
Var x, y;
Func f;
f(x, y) = x + y;

Implementations

Schedule #2

f.parallel(y);
f.vectorize(x, 8);
```

### Why use Halide as Front-End to Spatial?

### Separation of concerns

- High-level transformations: Tiling, Vectorization etc can happen in Halide
- Lift the hard work of transforming loop nests to Halide
- Optimized code can be lowered into spatial

### Loop-based IR

Easy mapping to Spatial front-end

### Halide IR

```
// Algorithm
Var x, y;
Func f;
f(x, y) = x + y;

// Schedule
f.parallel(y);
f.vectorize(x, 8);

f.realize(32, 32);
```

```
produce f {
 let t6 = (f.extent.0 + f.min.0)
 let t7 = (f.min.1*f.stride.1)
 let t8 = max((f.extent.0/8), 0)
 let t3 = (t8 < ((f.extent.0 + 7)/8))
 let t2 = (0 - t7)
 let t5 = (((t6 - t7) - f.min.0) + -8)
  let t4 = (t6 + -8)
  parallel (f.s0.y, f.min.1, f.extent.1) {
   let t10 = ((f.s0.y*f.stride.1) + t2)
   let t9 = (f.min.0 + f.s0.y)
    for (f.s0.x.x, 0, t8) {
      f[ramp(((f.s0.x.x*8) + t10), 1, 8)] = ramp(((f.s0.x.x*8) + t9), 1, 8)
   if (t3) {
      f[ramp(((f.s0.y*f.stride.1) + t5), 1, 8)] = ramp((f.s0.y + t4), 1, 8)
```

### **Example: Halide to Spatial**

```
// Algorithm
f(x, y) = x + y;
g(x, y) = (f(x, y) + f(x, y+1))/2;
// Schedule
g.in().spatial();
g.store_in(MemoryType::SRAM)
 .compute at(g.in(), Var::outermost());
g.tile(x, y, xo, yo, xi, yi, 4, 4);
f.compute root();
f.in()
 .copy to device()
 .store_in(MemoryType::SRAM)
 .compute at(g, xo);
g.in().copy_to_host();
wrapper.compile to spatial(...);
```

### **Example: Halide to Spatial**

```
// Algorithm
f(x, y) = x + y;
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f.in()
 .copy to device()
 .store in(MemoryType::SRAM)
 .compute at(g, xo);
g.in().copy to host();
wrapper.compile to spatial(...);
```

```
val g wrapper = DRAM[Int](16, 16);
Accel {
 val g = SRAM[Int](16, 16);
  Foreach(0 until 4 by 1) {yo =>
    Foreach(0 until 4 by 1) {xo =>
      val f wrapper = SRAM[Int](4, 5);
      f wrapper load f(xo*4::xo*4+4, yo*4::yo*4+5);
      Foreach(0 until 4 by 1) {yi =>
        Foreach(0 until 4 by 1) {xi =>
          q(xo*4+xi, yo*4+yi) =
            (f wrapper(xi,yi)+f wrapper(xi,yi+1))/2;
  g_wrapper store g;
```

### **Example: Halide to Spatial**

```
// Algorithm
                                 Compute at
f(x, y) = x + y;
g(x, y) = (f(x, y) + f(x, y+1))
                                 Accelerator
// Schedule
g.in().spatial();
g.store in(MemoryType::SRAM)
 .compute at(g.in(), Var::outermost());
g.tile(x, y, xo, yo, xi, yi, 4, 4);
f.compute root();
f.in()
 .copy to device()
 .store_in(MemoryType::SRAM)
 .compute at(q, xo);
g.in().copy to host();
wrapper.compile to spatial(...);
```

```
val g wrapper = DRAM(Int)(16, 16):
Accel {
  val g = SRAM[Int](16, 16);
  Foreach(0 until 4 by 1) {yo =>
    Foreach(0 until 4 by 1) {xo =>
      val f wrapper = SRAM[Int](4, 5);
      f wrapper load f(xo*4::xo*4+4, yo*4::yo*4+5);
      Foreach(0 until 4 by 1) {yi =>
        Foreach(0 until 4 by 1) {xi =>
          q(xo*4+xi, yo*4+yi) =
            (f wrapper(xi,yi)+f wrapper(xi,yi+1))/2;
  g wrapper store g;
```

```
Allocate SRAM
// Algorithm
                                    to store 'g'
f(x, y) = x + y;
g(x, y) = (f(x, y) + f(x, y+1))/2;
// Schedule
g.in().spatial();
g.store in(MemoryType::SRAM)
.compute at(g.in(), Var..outermost());
g.tile(x, y, xo, yo, xi, yi, 4, 4);
f.compute root();
f.in()
 .copy to device()
 .store_in(MemoryType::SRAM)
 .compute at(q, xo);
g.in().copy to host();
wrapper.compile to spatial(...);
```

```
val g wrapper = DRAM[Int](16, 16);
Accel
  val g = SRAM[Int](16, 16);
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    Foreach(0 until 4 by 1) {xo =>
      val f wrapper = SRAM[Int](4, 5);
      f wrapper load f(xo*4::xo*4+4, yo*4::yo*4+5);
      Foreach(0 until 4 by 1) {yi =>
        Foreach(0 until 4 by 1) {xi =>
          q(xo*4+xi, yo*4+yi) =
            (f wrapper(xi,yi)+f wrapper(xi,yi+1))/2;
  g wrapper store g;
```

```
// Algorithm
f(x, y) = x + y;
g(x, y) = (f(x, y) + f(x, y+1))/2;
                                         Tile g
// Schedule
g.in().spatial();
g.store in(MemoryType::SRAM)
 .compute at(g.in(), Var::outermost());
[g.tile(x, y, xo, yo, xi, yi, 4, 4);
f.compute root();
f.in()
 .copy to device()
 .store in(MemoryType::SRAM)
 .compute at(g, xo);
g.in().copy to host();
wrapper.compile to spatial(...);
```

```
val g wrapper = DRAM[Int](16, 16);
Accel {
 val g = SRAM[Int](16, 16);
 Foreach(0 until 4 by 1) {yo =>
   Foreach(0 until 4 by 1) {xo =>
      val f wrapper = SRAM[Int](4, 5);
      f wrapper load f(xo*4::xo*4+4, yo*4::yo*4+5);
     Foreach(0 until 4 by 1) {yi =>
       Foreach(0 until 4 by 1) {xi =>
          g(xo*4+xi, yo*4+yi) =
            (f wrapper(xi,yi)+f wrapper(xi,yi+1))/2;
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```

```
// Algorithm
f(x, y) = x + y;
g(x, y) = (f(x, y) + f(x, y+1))/2;
// Schedule
g.in().spatial();
g.store in(MemoryType::SRAM)
 .compute at(g.in(), Var::outermost());
g.tile(x, y, xo, yo, xi, yi, 4, 4);
                                      Load 'T' into
f.compute root();
                                           the
f.in()
                                      accelerator's
 .copy to device()
 .store_in(MemoryType::SRAM)
                                        memory
 .compute at(g, xo);
g.in().copy to host();
wrapper.compile to spatial(...);
```

```
val g wrapper = DRAM[Int](16, 16);
Accel {
 val g = SRAM[Int](16, 16);
  Foreach(0 until 4 by 1) {yo =>
    Foreach(0 until 4 by 1) {xo =>
      val f wrapper = SRAM[Int](4, 5);
      f wrapper load f(xo*4::xo*4+4, yo*4::yo*4+5);
      Foreach ( until 4 by 1) {y1 =>
       Foreach(0 until 4 by 1) {xi =>
          g(xo*4+xi, yo*4+yi) =
            (f_wrapper(xi,yi)+f_wrapper(xi,yi+1))/2;
  g_wrapper store g;
```

```
// Algorithm
f(x, y) = x + y;
g(x, y) = (f(x, y) + f(x, y+1))/2;
// Schedule
                              Do the load at loop
g.in().spatial();
                             level 'xo' and store
g.store in(MemoryType::SRAM)
 .compute at(g.in(), Var::out
                                    in SRAM
g.tile(x, y, xo, yo, xi, yi, 4, 4);
f.compute root();
f.in()
 .copy to device()
 .store in(MemoryType::SRAM)
 .compute at(g, xo);
g.in().copy_to_host();
wrapper.compile to spatial(...);
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        Foreach(0 until 4 by 1) {xi =>
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  g wrapper store g;
```

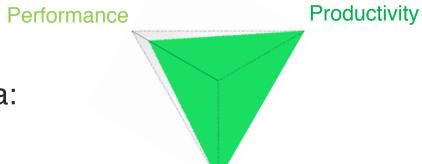
```
// Algorithm
                                                    val g wrapper = DRAM[Int](16, 16);
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                                                    Accel {
g(x, y) = (f(x, y) + f(x, y+1))/2;
                                                      val g = SRAM[Int](16, 16);
                                                      Foreach(0 until 4 by 1) {yo =>
// Schedule
                                                        Foreach(0 until 4 by 1) {xo =>
g.in().spatial();
                                                          val f wrapper = SRAM[Int](4, 5);
g.store_in(MemoryType::SRAM)
                                                          f wrapper load f(xo*4::xo*4+4, yo*4::yo*4+5);
 .compute at(g.in(), Var::outermost());
                                                          Foreach(0 until 4 by 1) {yi =>
g.tile(x, y, xo, yo, xi, yi, 4, 4);
                                                            Foreach(0 until 4 by 1) {xi =>
                                                              q(xo*4+xi, yo*4+yi) =
f.compute root();
                                                                (f wrapper(xi,yi)+f wrapper(xi,yi+1))/2;
f.in()
                                        Store 'g'
 .copy to device()
 .store in(MemoryType::SRAM)
                                        back into
 .compute at(g, xo);
                                      host's DRAM
                                                      <u>g_wrapper store g;</u>
g.in().copy_to_host();
wrapper.compile to spatial(...);
```

• Reconfigurable architectures are becoming key for performance / energy efficiency

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  - Design parameters for tuning
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- Spatial prototypes these language and compiler criteria:
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  - Average 42% less code than SDAccel
  - Achieves transparent portability through internal support for automated design to the high the support for automated design to the suppo



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**Performance** 



Spatial is open source: <a href="https://spatial-lang.org/">https://spatial-lang.org/</a>

**Productivity** 

# **Backup Slides**

#### **The Team**



**David** Koeplinger



**Matt** Feldman



**Raghu** Prabhakar



**Yaqi** Zhang



**Stefan** Hadjis



**Ruben** Fiszel



**Tian** Zhao



**Ardavan** Pedram



**Luigi** Nardi



**Christos** Kozyrakis

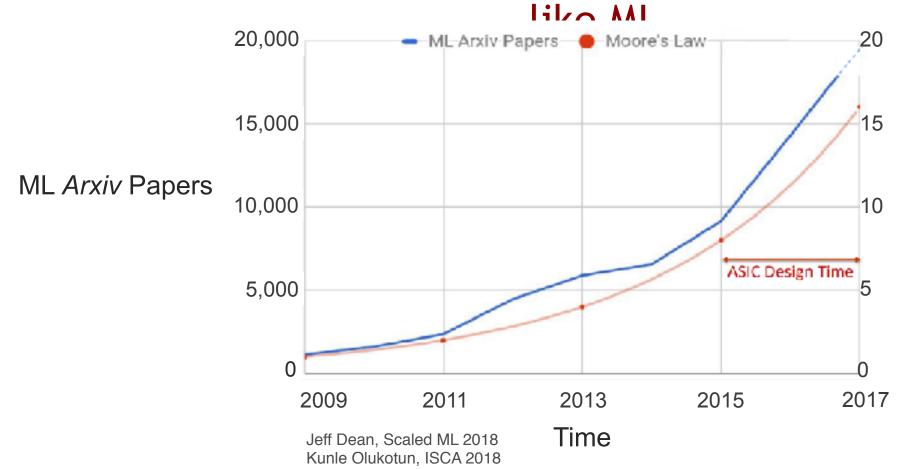


**Kunle** Olukotun

**Good** for widely used, **fixed** specifications (like compression)

**Good** for widely used, **fixed** specifications (like compression) **Expensive** with **long design turnaround** for developing fields like ML

Good for widely used, fixed specifications (like compression) Expensive with long design turnaround for developing fields



Relative # of Papers / Year Since 2009

#### Add 512 integers originating from accelerator DRAM

```
void sum(int* mem) {
    mem[512] = 0;

    for(int i=0; i < 512; i++) {
        mem[512] += mem[i];
    }
}</pre>
```

#### Add 512 integers originating from accelerator DRAM

```
void sum(int* mem) {
    mem[512] = 0;

    for(int i=0; i < 512; i++) {
        mem[512] += mem[i];
    }
}</pre>
```



#### Add 512 integers originating from external DRAM

```
#define CHUNKSIZE (sizeof(MPort)/sizeof(int))
#define LOOPCOUNT (512/CHUNKSIZE)
void sum(MPort* mem) {
    MPort buff[LOOPCOUNT];
    memcpy(buff, mem, LOOPCOUNT);
    int sum = 0;
    for(int i=1; i<LOOPCOUNT; i++) {</pre>
        #pragma PIPELINE
        for(int j=0; j<CHUNKSIZE; j++) {</pre>
             #pragma UNROLL
             sum += (int)
(buff[i]>>j*sizeof(int)*8);
    mem[512] = sum;
```

**Runtime: 302 clock cycles** 

#### Add 512 integers originating from external DRAM

```
#define CHUNKSIZE (sizeof(MPort)/sizeof(int))
                                                     Width of DRAM controller
    #define LOOPCOUNT (512/CHUNKSIZE)
                                                    interface
   void sum(MPort* mem) {
       MPort buff[LOOPCOUNT];
                                         Burst Access
        memcpy(buff, mem, LOOPCOUNT);
        int sum = 0; Use local variable
                                                Loop
        for(int i=1; i<LOOPCOUNT; i++) </pre>
                                                Restructurin
            #pragma PIPELINE
            for(int j=0; j<CHUNKSIZE; j++)</pre>
Special
                #pragma UNROLL
compiler
                sum += (int)
directives
           |>>j*sizeof(int)*8);
                                              Bit shifting to
                                              extract individual
                                              elements
        mem[512] = sum;
             Runtime: 302 clock cycles
```

1. Finite physical compute and memory resources

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- 2. Requires aggressive pipelining for performance
  - Maximize useful execution time of compute resources

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- 2. Requires aggressive pipelining for performance
  - Maximize useful execution time of compute resources
- 3. Disjoint memory space
  - No hardware managed memory hierarchy
- 4. Huge design parameter spaces
  - Parameters are interdependent, change runtime by orders of magnitude
- 5. Others... pipeline timing, clocking, etc.

```
Foreach(N by 1) { r \Rightarrow
  val a = SRAM[Float](D)
  val b = SRAM[Float](D)
  val c = SRAM[Float](D)
  Foreach(D par 2){i =>
    a(i) = ...
  Reduce(sum)(D par 2){j =>
    a(b(j))
  \{(a,b) => a + b\}
  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

```
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  val b = SRAM[Float](D)
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a

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Foreach(N by 1) { r \Rightarrow
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  Foreach(D par 2){i =>
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  Reduce(sum)(D par 2){j =>
    a(b(j))
  \{(a,b) => a + b\}
  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

```
Foreach{i =>
  2i
2i+1
Reduce{j =>
b(2j) ←
b(2j+1)←
Foreach{k =>
2k
2k+1
```

```
Foreach(N by 1) { r \Rightarrow
 val a = SRAM[Float](D)
  val b = SRAM[Float](D)
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  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

```
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2k
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```

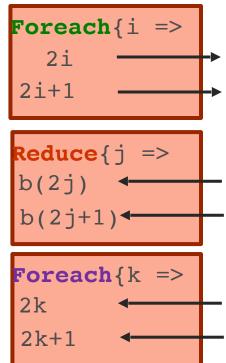


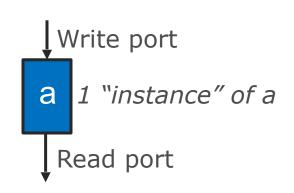
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  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

#### **Step 1:** For each read:

Find the **banking** and **buffering** for that read

and all writes that may be visible to that





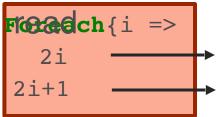
# Local Memory Analysis Example (Cont.)

```
Foreach(N by 1) { r \Rightarrow
  val a = SRAM[Float](D)
  val b = SRAM[Float](D)
  val c = SRAM[Float](D)
  Foreach(D par 2){i =>
    a(i) = ...
  Reduce(sum)(D par 2){j =>
    a(b(j))
  \{(a,b) => a + b\}
  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

#### Step 1: For each read:

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```
Reduce{j => b(2j) ← b(2j+1) ← b(2j+
```

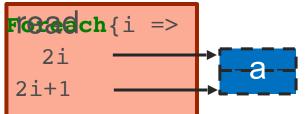
# Local Memory Analysis Example (Cont.)

```
Foreach(N by 1) { r \Rightarrow
  val a = SRAM[Float](D)
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  val c = SRAM[Float](D)
  Foreach(D par 2){i =>
    a(i) = ...
  Reduce(sum)(D par 2){j =>
    a(b(j))
  \{(a,b) => a + b\}
  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

#### Step 1: For each read:

Find the **banking** and **buffering** for that read

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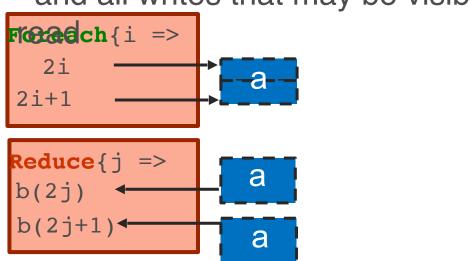
```
Reduce{j =>
b(2j) ◀
b(2j+1)◀
```

```
Foreach(N by 1) { r \Rightarrow
  val a = SRAM[Float](D)
  val b = SRAM[Float](D)
  val c = SRAM[Float](D)
  Foreach(D par 2){i =>
    a(i) = ...
  Reduce(sum)(D par 2){j =>
    a(b(j))
  \{(a,b) => a + b\}
  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```

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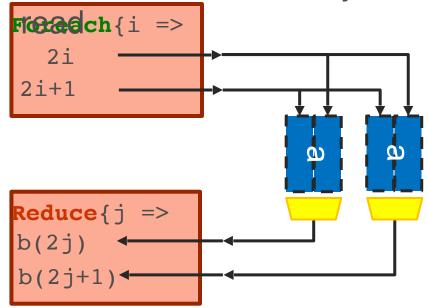


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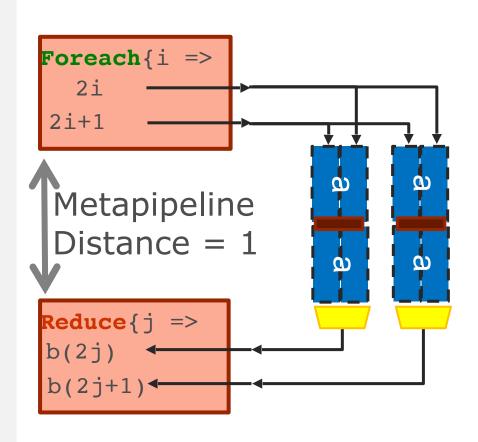
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Find the **banking** and **buffering** for that read

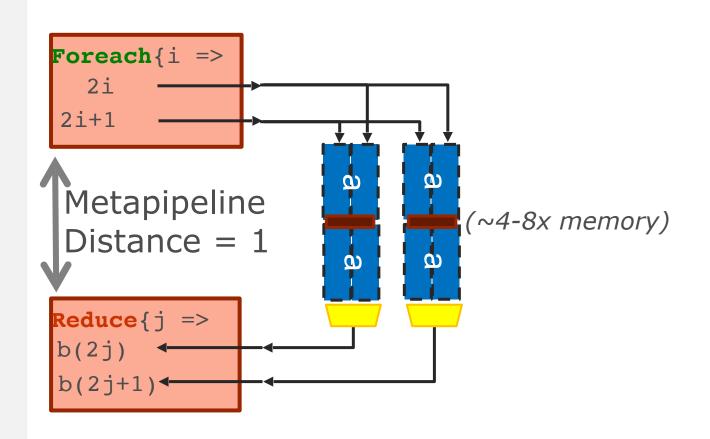
and all writes that may be visible to that



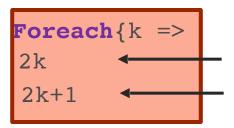
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Foreach(N by 1) { r \Rightarrow
  val a = SRAM[Float](D)
  val b = SRAM[Float](D)
  val c = SRAM[Float](D)
  Foreach(D par 2){i =>
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  Reduce(sum)(D par 2){j =>
    a(b(j))
  \{(a,b) => a + b\}
  Foreach(D par 2){k =>
    c(k) = a(k) * sum
```



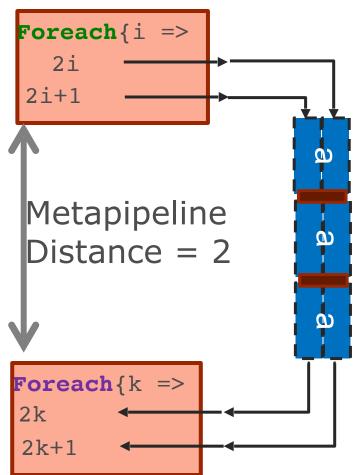
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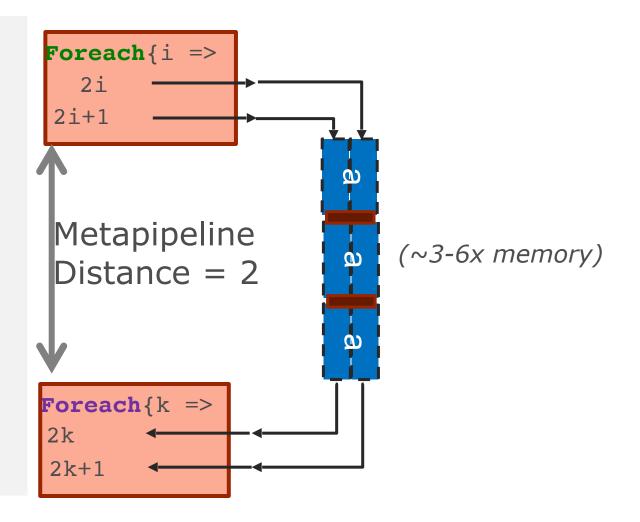
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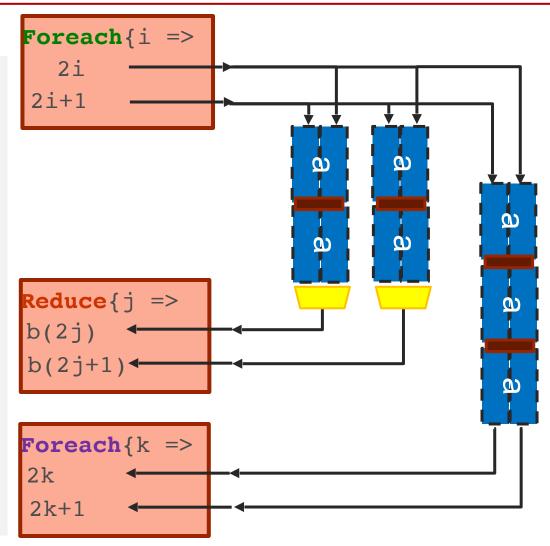
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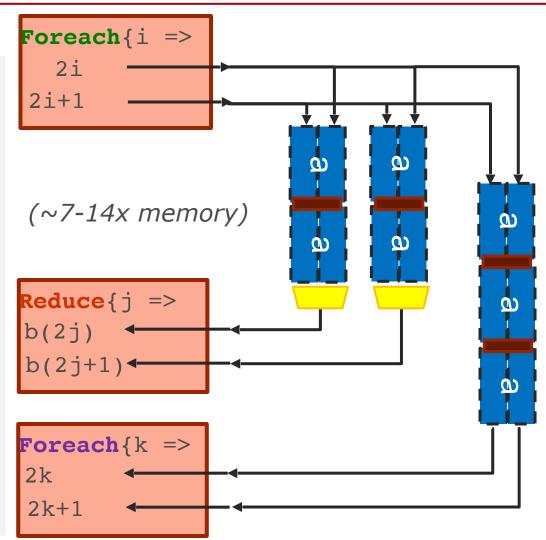
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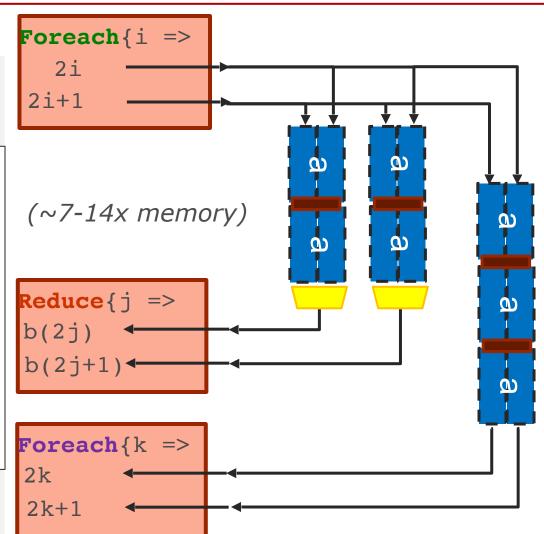


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**Step 2:** Greedily combine (merge) instances

- Don't combine if there are port conflicts
- Don't combine if the cost of merging is greater than sum of unmerged
- \*\*Recompute banking for merged instances!

```
}
```



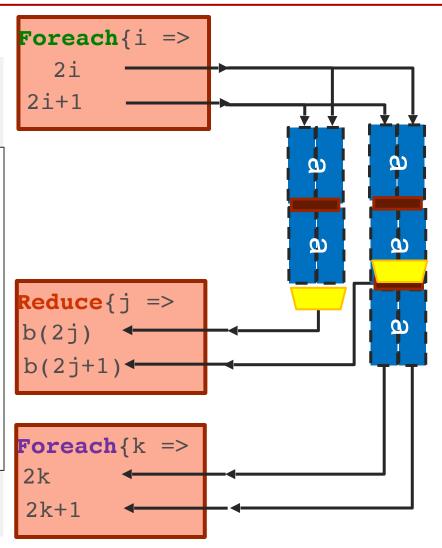
## **Local Memory Analysis**

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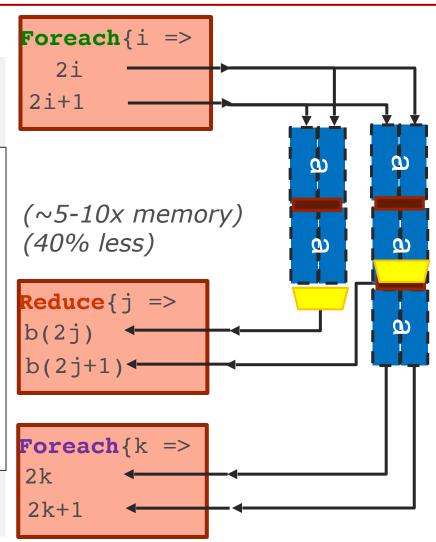
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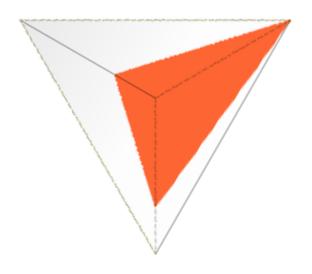
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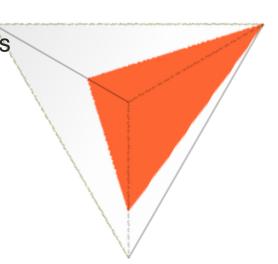
Manually implement each DSL operation; use a simple compiler to stitch them together



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#### Performance

Misses cross-kernel optimizations Excessive memory transfers Excessive buffering



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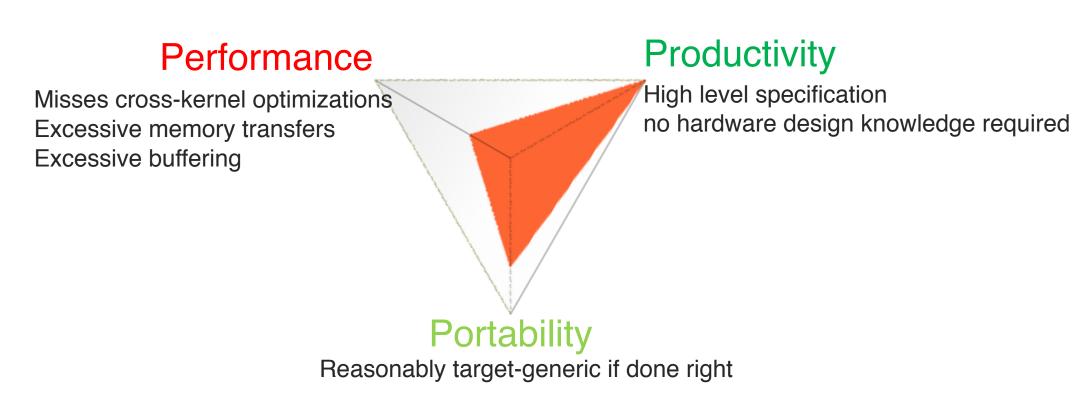
#### Performance

Misses cross-kernel optimizations Excessive memory transfers Excessive buffering

#### **Productivity**

High level specification no hardware design knowledge required

# Manually implement each DSL operation; use a simple compiler to stitch them together



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1 type TM = FixPt[TRUE, 9, 23]
  type TX = FixPt[TRUE, 9, 7]
 4|val| data = DRAM[TX](N, D)
 5 | val y = DRAM[TM](N)
 6 val weights = DRAM[TM](D)
 8 Accel {
    val yAddr = Reg[Int](-1)
    val yCache = SRAM[TM](CSIZE)
    val WK = SRAM[TM](D)
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    wK load weights(0::D)
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- On-chip memory allocations
- **Explicit** memory transfer
- Declaration of a sequential loop
- Debugging breakpoint
- **Explicit** memory transfer

```
22 def epoch(i: Int, ...): Unit = {
23
    val yPt = Reg[TM]
    if (i >= yAddr & i < yAddr+CSIZE & yAddr != -1) {</pre>
24
      yPt := yCache(i - yAddr)
25
26
27
    else {
28
     yAddr := i - (i % CSIZE)
     yCache load y(yAddr::yAddr + CSIZE)
29
      yPt := yCache(i % CSIZE)
30
31
32
33
    val x = SRAM[TX](D)
34
    x load data(i, 0::D)
35
36
    // Compute gradient against wK t
37
    val yHat = Reg[TM]
    Reduce(yHat)(D by 1){j \Rightarrow wK(j) * x(j).to[TM]}
38
39 { + }
40
    val yErr = yHat - yPt
41
42
    // Update wK t with reduced variance update
    Foreach(D by 1){i =>
43
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      wK(i) = wK(i) - (A.to[TM] * yErr * x(i).to[TM])
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Custom caching for random access on *y* 

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Custom caching for random access on y

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- Gradient computation

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Custom caching for random access on y

- Explicit memory transfer
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Weight update

# **SGD** in Spatial: Hardware

