

# Terapixel Image Processing and Simulation with Distributed Halide

by

Tyler Denniston

B.S. Computer Science  
Northeastern University (2012)

Submitted to the Department of Electrical Engineering and Computer Science  
in partial fulfillment of the requirements for the degree of

Master of Science

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

February 2016

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Author .....  
Department of Electrical Engineering and Computer Science  
January 29, 2016

Certified by .....  
Saman Amarasinghe  
Professor of Electrical Engineering and Computer Science  
Thesis Supervisor

Accepted by .....  
Leslie A. Kolodziejski  
Professor  
Chair of the Committee on Graduate Students



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Submitted to the Department of Electrical Engineering and Computer Science on January 29, 2016  
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## ABSTRACT

Many image processing and simulation tasks are naturally expressed as a pipeline of small computational kernels known as stencils. Halide is a popular domain-specific language and compiler designed to implement stencil algorithms. Halide uses simple language constructs to express what to compute and a separate scheduling co-language for expressing how to perform the computation. This approach has demonstrated performance comparable to or better than hand-optimized code. Until now, Halide has been restricted to parallel shared memory execution, limiting its performance and applicability to tomorrow's terapixel image processing tasks.

In this thesis we present an extension to Halide to support distributed-memory parallel execution of stencil pipelines. These extensions compose with the existing scheduling constructs in Halide, allowing expression of complex computation and communication strategies. Existing Halide applications can be distributed with minimal changes, allowing programmers to explore the tradeoff between recomputation and communication with little effort. Approximately 10 new lines of code are needed even for a 200 line, 99 stage application.

On nine image processing benchmarks, my extensions give up to a  $1.4\times$  speedup on the same number of cores over regular multithreaded execution by mitigating the effects of non-uniform memory access. The image processing benchmarks achieve up to  $18\times$  speedup on a 16 node testing machine and up to  $57\times$  speedup on 64 nodes of the NERSC Cori supercomputer. A 3D heat finite-difference simulation benchmark achieves linear scaling from 64 to 512 Cori nodes on a  $10,000^3$ , or 1 terapixel, input. We also demonstrate scalability results for two of the image processing benchmarks on 1 terapixel inputs, and make the argument that supporting such large scale is essential for tomorrow's image processing and simulation needs.

Thesis Supervisor: Saman Amarasinghe

Title: Professor of Electrical Engineering and Computer Science



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## ACKNOWLEDGEMENTS

The road to this thesis was difficult, and one person who put up with my late nights, early mornings, and general grumpiness deserves particular thanks. Without the unfailing support, understanding and love of my wife, Charliss, I certainly could not have gotten to this point or survived with wits intact: I cannot thank you enough! My parents and brother also played a central role in providing the support necessary to accomplish the work described in this thesis. I would also like to thank my friends and labmates Fredrik Kjølstad and Aparna Chandramowliswaran for many intriguing discussions and occasional comic relief.

On a more technical note, I would like to thank Shoaib Kamil, Vlad Kiriansky and my advisor Saman Amarasinghe for their invaluable help in designing experiments and interpreting their results. Without their help and insight, this work would likely still be an unintelligible pile of numbers. Finally, I would like to thank my undergraduate research advisor and mentor, Professor Gene Cooperman, whose lessons and advice I still use and lean on daily.



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# Chapter 1

## Introduction

High-throughput and low-latency image processing algorithms are of increasing importance due to their wide applicability in fields such as computer graphics and vision, scientific and medical visualization, and consumer photography. The resolution and framerate of images that must be processed is rapidly increasing with the improvement of camera technology and the falling cost of storage space. For example, the Digitized Sky Survey [1] is a collection of several thousand images of the night sky, ranging in resolution from  $14,000 \times 14,000$  to  $23,040 \times 23,040$  pixels, or 200 to 500 megapixels. Canon, a consumer-grade camera manufacturer, recently introduced a 250 megapixel image sensor [2]. Processing such large images is a non-trivial task: on modern multicore hardware, a medium-complexity filter such as a bilateral grid [13] can easily take up to 10 seconds for a 500 megapixel image.

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While today's typical image sizes may be in the mega- to gigapixel range, the world is rapidly approaching a point where terapixel-sized inputs will be more commonplace. Particularly in satellite and celestial imaging there are already numerous projects to provide interactive exploration of monolithic terapixel images, e.g. [18, 4]. However, preprocessing of these terapixel images is a daunting task; the techniques used in [18] took approximately 7 hours on 512 cores to produce the final 802GB terapixel image. As this scale of image processing becomes more common, the need for a dedicated language and framework increases.

A widely used class of scientific simulations known as finite-difference simulations are on a similar trajectory. The modern approach to problem solving in medical, physical and environmental sciences often begins with the simulation of a new drug or model. As the science progresses, the required simulations quickly become intractable to solve except with the dedicated use of a supercomputer. Supporting terapixel-sized domains could mean the difference between simulating a single blood vessel versus the entire heart, or higher resolution and more accurate weather predictions. By making it possible for scientists to quickly and easily solve these types of problems on a very large scale, the pace of scientific advancement can increase.

Halide [31] is a popular domain-specific language for high-performance stencil pipelines, used in Google+ Photos, and the Android and Glass platforms [30]. A major advantage of Halide is that it separates *what* is being computed (the algorithm) from *how* it is computed (the schedule), enabling programmers to write the

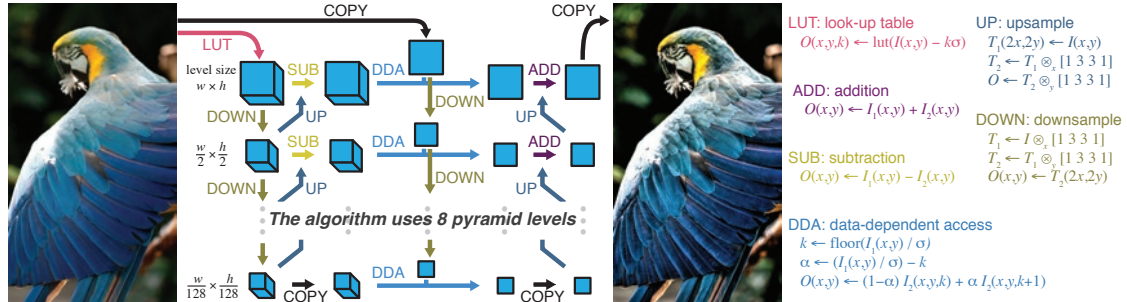


Figure 1.1: Data dependencies in a local Laplacian filter. Each box represents intermediate data, and arrows represent functions (color-coded with their bodies on the right) defining the data. Image reproduced with permission from [31].

algorithm once in a high-level language, and then quickly try different strategies to find a high-performing schedule. Halide code often outperforms hand-written expert-optimized implementations of the same algorithm. Although originally intended for image processing, the stencil model of computation can be directly applied to finite-difference simulations, a very common and widely used class.

When many stencils are composed into deep pipelines such as the local Laplacian filter [29], the inter-stage data dependencies easily become very complex, as visualized in Figure 1.1. In the case of a local Laplacian filter, many different re-sampling, data-dependent gathers and horizontal and vertical stencils combine to create a complex network of dependencies. Such complexity makes rewriting a program to experiment with different optimization strategies for computation extremely time consuming. A programmer can easily explore this space with Halide’s separation of algorithm and schedule.

Halide is currently limited to shared-memory execution. For the common

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case where a stencil pipeline is memory-bandwidth bound, the performance ceiling of these tasks is solely determined by the memory bandwidth of the executing system. Adding additional parallelism with more threads for such pipelines therefore does not result in higher performance. And, with modern multi-socket platforms embracing a non-uniform memory access (NUMA) architecture, simplistic parallel scheduling such as the work queue used by Halide often achieves poor parallel efficiency due to frequent misses into remote memory or cache. Additionally, even typical supercomputing platforms contain less than 128 to 256 GB of main memory per node, limiting the total problem size that can be easily tackled on a single shared-memory machine.

We address this challenge with our distributed language and compiler extensions. By augmenting Halide programs with the ability to seamlessly distribute data and execution across many compute nodes, distributed Halide offers the ability to overcome the limitations of shared-memory pipelines with very little effort. Distributed Halide pipelines gain access to more parallelism and increased memory bandwidth, and exhibit better hardware utilization of each individual node. The language extensions for distribution fit well within the existing scheduling language constructs, which can still be used to explore schedules for the on-node computation. The ability to use the a single scheduling language for both distribution and on-node scheduling is important, since depending on the distribution strategy, different on-node schedules yield the best overall performance.

---

## Contributions

In this thesis, we present language extensions for distributing pipelines and a new compiler backend that generates distributed code. In particular, the contributions are:

- A Halide language extension for distributing image processing pipelines, requiring programmers to write only approximately 10 new lines of code. We show that it is possible to describe complex organizations of data and computation both on-node and across multiple machines using a single, unified scheduling language.
- The implementation of a Halide compiler backend generating distributed code via calls to an MPI library.
- A demonstration of how distributed pipelines can achieve a  $1.4\times$  speedup on a single node with the same number of cores over regular multithreaded execution by mitigating NUMA effects.
- Evaluation of nine distributed image processing benchmarks scaling up to 2,048 cores, with an exploration of redundant work versus communication tradeoff.
- Evaluation of two image processing benchmarks and one simulation benchmark on terapixel-sized input, scaling up to 16,384 cores.

---

The rest of this thesis is organized as follows. Chapter 2 summarizes the necessary background on Halide including simple scheduling semantics. Chapter 3 introduces the new distributed scheduling directives and Chapter 4 discusses distributed code generation. Chapter 5 evaluates distributed Halide on several benchmarks. Chapter 6 discusses related work, and Chapter 7 concludes. Appendix A contains a brief tutorial on the new language features.



## Chapter 2

# Halide Background

Halide [31] is a domain-specific language embedded in C++ for image processing. One of its main points of novelty is the fundamental, language-level separation between the algorithm and schedule for a given image processing pipeline. The algorithm specifies what is being computed, and the schedule specifies how the computation takes place. By separating these concerns in the language, a programmer only writes an algorithm once. When hardware requirements change, or new features such as larger vector registers or larger caches become available, the programmer must only modify the schedule to take advantage of them.

As a concrete example, consider a simple  $3 \times 3$  box blur. One typical method to compute this is a 9-point stencil, computing an output pixel as the average value of the neighboring input pixels. In Halide, such a blur can be expressed in two stages: first a horizontal blur over a  $1 \times 3$  region of input pixels, followed

---

by a vertical  $3 \times 1$  blur. This defines the algorithm of the blur, and is expressed in Halide as:

```
bh(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y)) / 3;
bv(x, y) = (bh(x, y-1) + bh(x, y) + bh(x, y+1)) / 3;
```

where each output pixel  $\text{output}(x, y) = \text{bv}(x, y)$ .

Halide schedules express how a pipeline executes. For example, one natural schedule computes the entire `bh` horizontal blur stage before computing the `bv` stage. In Halide's scheduling language, this is known as computing the function at "root" level, and is expressed as:

```
bh.compute_root();
```

With this schedule, our blur pipeline is compiled to the following pseudo-code of memory allocations and loop nests:

```
allocate bh[]
for y:
  for x:
    bh[y][x] = (in[y][x-1] + in[y][x] + in[y][x+1]) / 3
for y:
  for x:
    bv[y][x] = (bh[y-1][x] + bh[y][x] + bh[y+1][x]) / 3
```

By opting to completely compute the horizontal blur before beginning the vertical blur, we schedule the pipeline such that there is no redundant computation: each intermediate pixel in `bh` is only calculated once. However, this sacrifices

---

temporal locality. A pixel stored into the `bh` temporary buffer may not be available in higher levels of the memory hierarchy by the time it is needed to compute `bv`. This time difference is known as *reuse distance*: a low reuse distance is equivalent to good temporal locality.

Because the horizontal blur is so cheap to compute, a better schedule may compute some pixels of `bh` multiple times to improve reuse distance. One possibility is to compute a subset of the horizontal blur for every row of the vertical blur. Because a single row of the vertical blur requires three rows in `bh` (the row itself and the rows above and below), we can compute only those three rows of `bh` in each iteration of `bv.y`. In Halide, the schedule:

```
bh.compute_at(bv, y);
```

is lowered to the loop nest:

```
for y:
    allocate bh[]
    for y' from y-1 to y+1:
        for x:
            bh[y'][x] = (in[y'][x-1] + in[y'][x] + in[y'][x+1]) / 3
    for x:
        bv[y][x] = (bh[y-1][x] + bh[y][x] + bh[y+1][x]) / 3
```

Note that the inner iteration of `y'` ranges from `y-1` to `y+1`: the inner loop nest is calculating the currently needed three rows of `bh`. Some details such as buffer indexing and how the Halide compiler determines loop bounds have been elided here for clarity, but the essence is the same. The tradeoff explored by these two

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schedules is that of *recomputation versus locality*. In the first schedule, there is no recomputation, but locality suffers, while in the second schedule, locality improves, as values in `bh` are computed soon before they are needed, but we redundantly compute rows of `bh`.

Halide also offers a simple mechanism for adding parallelism to pipelines on a per-stage per-dimension basis. To compute rows of output pixels in parallel, the schedule becomes:

```
bh.compute_at(bv, y);  
bv.parallel(y);
```

which is lowered to the same loop nest as above, but with the outermost `bv.y` loop now a parallel for loop. The Halide compiler generates a function with the body of the parallel loop parameterized by the value of the induction variable (here `bv.y`). At runtime, a closure is created of this function for each value of the induction variable, and inserted into a work queue. Threads from a thread pool (implemented using, for example, `pthread`s) pull iterations from the work queue and execute them in parallel. This dynamic scheduling of parallelism can be a source of cache inefficiencies or NUMA effects, as we explore in Chapter 5. In particular, there is no effort to schedule parallel iterations according to spatial locality in the induction variable domain, potentially leading to poor use of cache.

Designing good schedules in general is a non-trivial task. For the  $3 \times 3$  box blur the most efficient schedule we have found, and the one we compare against in the evaluation is the following:

---

```
bh.store_at(bv, y).compute_at(bv, yi).vectorize(x, 8);  
bv.split(y, y, yi, 8).vectorize(x, 8).parallel(y);
```

For large pipelines such as the local Laplacian benchmark consisting of approximately 100 stages, the space of possible schedules is enormous.

One solution to the problem of finding schedules is applying an autotuning system to automatically search for efficient schedules, as was explored in [31]. Other more recent autotuning systems such as OpenTuner [10] could also be applied to the same end. Empirically, however, autotuning schedules for complex pipelines is not a realistic solution. For one complex pipeline we ran the autotuner for a full week on a dedicated machine; by the end of the week the autotuner had not even found a valid schedule. When we decomposed the problem and allowed the autotuner to search for schedules for only individual stages of the pipeline, it did discover valid schedules. However, when evaluating the autotuned schedule inside of the full pipeline, the net result was actually slower execution. Potential solutions to this problem are described (as future work) in Chapter 7. Until these problems are solved, manual experimentation is the preferred method to design efficient schedules.

## Chapter 3

# Distributed Scheduling

One of the major benefits of the algorithm plus schedule approach taken by Halide is the ability to quickly experiment to find an efficient schedule for a particular pipeline. In keeping with this philosophy, we designed the distributed Halide language extensions to be powerful enough to express complex computation and communication schemes, but simple enough to require very little effort to find a high-performance distributed schedule.

There are many possible language-level approaches to express data and computation distributions. We strove to ensure that the new scheduling constructs would compose well with the existing language both in technical (i.e. the existing compiler should not need extensive modification) and usability terms. The new extensions needed to be simple enough for programmers to easily grasp but powerful enough to express major tradeoffs present in distributed-memory pro-

grams.

Striking a balance between these two points was accomplished by adding two new scheduling directives, `distribute()` and `compute_rank()`, as well as a new data type, `DistributedImage`, that uses a simple syntax to specify data distributions. In this chapter we will show that these extensions are simple to understand, compose with the existing language, and allow complex pipelines to be scheduled for excellent scalability.

## 3.1 Data Distribution via `DistributedImage`

Input and output buffers in Halide are represented using the user-facing `Image` type. Images are multidimensional Cartesian grids of pixels and support simple methods to access and modify pixel values at given coordinates. In distributed Halide, we implemented a user-facing `DistributedImage` buffer type which supports additional methods to specify the distribution of data to reside in the buffer.

A `DistributedImage` is declared by the user with the dimensions' global extents and names. A data distribution for each `DistributedImage` is specified by the user by using the `placement()` method, which returns an object supporting a subset of the scheduling directives used for scheduling Halide functions, including the new `distribute()` directive. "Scheduling" the placement specifies a data distribution for that image. Once a data distribution has been specified,

### 3.1. Data Distribution via `DistributedImage`

---

memory can be allocated for the local region of the `DistributedImage`. The following example declares a `DistributedImage` with global extents `width` and `height` but distributed along the `y` dimension.

```
DistributedImage<int> input(width, height);
input.set_domain(x, y);
input.placement().distribute(y);
input.allocate();
```

It is important to note that the amount of backing memory allocated on each rank with the `allocate()` call is only the amount of the per-rank size of the image. The size of the local region is determined by the logic explained next in Section 3.2. The call to `allocate()` must occur separately and after all scheduling has been done via `placement()` in order to calculate the per-rank size.

For a rank to initialize its input image, the `DistributedImage` type supports conversion of local buffer coordinates to global coordinates and vice versa. This design supports flexible physical data distributions. For example, if a monolithic input image is globally available on a distributed file system, each rank can read only its local portion from the distributed file system by using the global coordinates of the local region. Or, if input data is generated algorithmically, each rank can initialize its data independently using local or global coordinates as needed. In either case, at no point does an individual rank allocate or initialize the entire global image. Output data distribution is specified in exactly the same manner.



## 3.2 Computation Distribution

To support scheduling of distributed computations, we introduce two new scheduling directives: `distribute()` and `compute_rank()`.

The `distribute()` directive is applied to dimensions of individual pipeline stages, meaning each stage may be distributed independently of other stages. Because dimensions in Halide correspond directly to levels in a loop nest, a distributed dimension corresponds to a distributed loop in the final loop nest. The iteration space of a distributed loop dimension is split into slices according to a block distribution. Each rank is responsible for exactly one contiguous slice of iterations of the original loop dimension.

The `compute_rank()` directive is applied to an entire pipeline stage, specifying that the computed region of the stage is the region required by all of its consumers on the local rank (we adopt the MPI terminology “rank” to mean the ID of a distributed process). Scheduling a pipeline stage with `compute_rank()` ensures that locally there will be no redundant computation, similar to the semantics of `compute_root()` in existing Halide. However, different ranks may redundantly compute some regions of `compute_rank()` functions. Therefore, `compute_rank()` allows the expression of globally redundant but locally nonredundant computation, a new point in the Halide scheduling tradeoff space. This is explored in more detail in Section 3.4.

The block distribution is defined as follows. Let  $R$  be the number of MPI

processes or ranks available and let  $w$  be the global extent of a loop dimension being distributed. Then the slice size  $s = \lceil w/R \rceil$ , and each rank  $r$  is responsible for iterations

$$[rs, \min(w, (r + 1)s))$$

where  $[u, v)$  denotes the half-open interval from  $u$  to  $v$ . This has the effect of assigning the last rank fewer iterations in the event  $R$  does not evenly divide  $w$ .

The slicing of the iteration space is parameterized by the total number of ranks  $R$  and the current rank  $r$ . The code generation (explained in Chapter 4) uses symbolic values for these parameters; thus, running a distributed Halide pipeline on different numbers of ranks does not require recompiling the pipeline.

The `distribute()` directive can also be applied to two or three dimensions of a function to specify multidimensional (or *nested*) distribution. For nested distribution, the user must specify the size of the desired processor grid to distribute over: currently, parametric nested distributions as in the one dimensional case are not supported. The nested block distribution is defined as follows. Let  $x$  and  $y$  respectively be the inner and outer dimensions in a 2D nested distribution, let  $w$  and  $h$  be their respective global extents and let  $a$  and  $b$  be the respective extents of the specified processor grid. Then the slice sizes are  $s_x = \lceil w/a \rceil$  and  $s_y = \lceil h/b \rceil$ . Each rank  $r$  is responsible for a 2D section of the original iteration space, namely:

$$\begin{aligned} x &\in [r \pmod{a}s_x, \min(w, (r \pmod{a} + 1)s_x)) \\ y &\in [(r \setminus a)s_y, \min(h, (r \setminus a + 1)s_y)) \end{aligned}$$

where  $u \setminus v$  denotes integer division of  $u$  and  $v$ . For 3D distribution, letting  $d$  be the extent of the third dimension  $z$ ,  $c$  be the third extent of the specified processor grid,  $s_z = \lceil d/c \rceil$ , the iteration space for rank  $r$  is:

$$\begin{aligned}
 x &\in [(r \pmod{ab}) \pmod{a} s_x, \\
 &\quad \min(w, ((r \pmod{ab}) \pmod{a} + 1) s_x)) \\
 y &\in [((r \pmod{ab}) \setminus a) s_y, \\
 &\quad \min(h, (((r \pmod{ab}) \setminus a) + 1) s_y)) \\
 z &\in [(r \setminus (ab)) s_z, \min(d, (r \setminus (ab) + 1) s_z)].
 \end{aligned}$$

Supporting nested distribution is essential for scalability due to the well-known surface area vs. volume effect; nested distribution reduces the overall amount of communication required for a pipeline versus a one-dimensional distribution as the number of ranks increases. In distributed stencil computations, the surface area of the iteration space “chunk” correlates directly to the amount of communication needed for the border exchange, and the volume correlates to the amount of local computation that can be performed. By minimizing the ratio of surface area to volume, one minimizes the ratio of communication versus computation, a quality necessary to achieve good scaling properties.

Consider as an example a two-dimensional input of size  $n \times n$ . Given  $R$  ranks, a one-dimensional distribution of this input would have volume  $V_1 = \frac{n^2}{R}$  and

surface area  $S_1 = 2n$ . Then the surface area to volume ratio

$$\frac{S_1}{V_1} = 2n \cdot \frac{R}{n^2} = \frac{2R}{n}.$$

The same input with a 2D nested distribution across a  $\sqrt{R} \times \sqrt{R}$  processor grid would have volume  $V_2 = \frac{n}{\sqrt{R}} \cdot \frac{n}{\sqrt{R}} = \frac{n^2}{R}$ , the same as  $V_1$ . However, the surface area  $S_2 = \frac{4n}{\sqrt{R}}$ , yielding a surface area to volume ratio

$$\frac{S_2}{V_2} = \frac{4\sqrt{R}}{n}.$$

Therefore, the 2D nested distribution is preferred when

$$\begin{aligned} \frac{S_2}{V_2} &< \frac{S_1}{V_1} \\ \frac{4\sqrt{R}}{n} &< \frac{2R}{n} \\ 4 &< R. \end{aligned}$$

A similar argument can be made for 3D versus 2D. Other discussion and analysis can be found in the literature on this topic, for example in [24].

When  $R$  is not a perfect square, the size of the processor grid should be chosen to come as close to  $\sqrt{R}$  on each dimension as possible, to minimize the surface area and maximize the number of utilized processors. In particular, for non-square  $R$ , we wish to find  $a, b$  such that  $ab \leq R$ , and  $|a - \sqrt{R}|$  and  $|b - \sqrt{R}|$  are minimized. Then the processor grid size is  $a \times b$ . For 3D distribution and non-cube  $R$  we wish to find  $a, b, c$  such that  $abc \leq R$ , and  $|a - \sqrt[3]{R}|, |b - \sqrt[3]{R}|, |c - \sqrt[3]{R}|$

are all minimized. The following algorithms APPROXFACTORSNEARSQRT and APPROXFACTORSNEARCUBERT determine these values iteratively.

---

**Algorithm** APPROXFACTORSNEARSQRT

**Input** Number of ranks  $R$

**Output** Pair of integers  $(a, b)$  such that  $ab \leq R$  and  $|a - \sqrt{R}|, |b - \sqrt{R}|$  are minimized.

1. **Let**  $s = \lfloor \sqrt{R} \rfloor$
  2. **If**  $s \cdot s = R$  **then return**  $(s, s)$ .
  3. **While**  $s > 0$  **do**
    - a) **Let**  $a = R \setminus s, b = R \setminus a$ .
    - b) **If**  $a \cdot b \leq R$  **then break**.
    - c) **Else let**  $s = s - 1$ .
  4. **Return**  $(a, b)$ .
-

**Algorithm** APPROXFACTORSNEARCUBERT

**Input** Number of ranks  $R$

**Output** Triple of integers  $(a, b, c)$  such that  $abc \leq R$  and  $|a - \sqrt[3]{R}|, |b - \sqrt[3]{R}|, |c - \sqrt[3]{R}|$  are minimized.

1. **Let**  $s = \lfloor \sqrt[3]{R} \rfloor$
  2. **If**  $s \cdot s \cdot s = R$  **then return**  $(s, s, s)$ .
  3. **While**  $s > 0$  **do**
    - a) **Let**  $(a, b) = \text{APPROXFACTORSNEARSQRT}(R \setminus s)$ .
    - b) **Let**  $c = R \setminus (ab)$ .
    - c) **If**  $a > 0, b > 0, c > 0$  **and**  $abc \leq R$  **then break**.
    - d) **Else let**  $s = s - 1$ .
  4. **Return**  $(a, b, c)$ .
- 

Coupling this analysis with the ease of programming in distributed Halide yields an effective solution for well-performing pipelines at any scale. While not yet implemented, in principle one could use the existing Halide `specialize()` scheduling directive to apply a one- or two-dimensional distribution depending on the number of ranks available at runtime. The `specialize()` directive takes as an argument a predicate that can be evaluated at runtime, and only applies the subsequent scheduling transformations if the predicate is true. A pipeline utilizing this technique might then be:

```
f(x, y) = ...;
f.compute_root();
Pair p = ApproxFactorsNearSqrt(num_ranks);
f.distribute(y).specialize(num_ranks > 4)
    .distribute(x, y, p.a, p.b);
```

Traditional distributed applications or libraries supporting this type of dynamism would require programmers to implement and maintain both code paths; with distributed Halide it would become a matter of changing a single line of code.

Finally, supporting parametric nested distribution (i.e. letting the user omit the processor grid size) could be done by code generating a runtime call to `APPROXFACTORSNEARSQRT` or `APPROXFACTORSNEARCUBERT` to determine values for parameters  $a, b$  or  $a, b, c$ . Then the scheduling syntax for nested distribution would directly mirror one-dimensional scheduling, i.e. one could write:

```
f(x, y) = ...;
f.compute_root();
f.distribute(y).specialize(num_ranks > 4).distribute(x, y);
```

This syntactic sugar has not yet been implemented.

## 3.3 Introductory Example

As an example, consider a simple one-dimensional blur operation:

```
f(x) = (input(x - 1) + input(x + 1)) / 2;
```

We can distribute this single-stage pipeline using the two new language features (eliding the boilerplate `set_domain()` and `allocate()` calls):

```
DistributedImage input(width);
input.placement().distribute(x);
f.distribute(x);
```

With this schedule, the `input` buffer is distributed along the same dimension as its consumer stage `f`.

We call the slice of the `input` buffer residing on each rank the *owned region*. Because `f` is a stencil, we must also take into account the fact that to compute an output pixel `f(x)` requires `input(x-1)` and `input(x+1)`. We denote this the *required region* of buffer `input`.

Suppose that the width of `input` is 10 pixels, and we have 3 ranks to distribute across. Then Table 3.1 enumerates each rank's owned and required regions of `input`, according to the distributed schedule. Because the `input` buffer is distributed independently from its consumer, and distributed slices are always disjoint by construction, the required region is larger than the owned region for buffer `input`. Therefore, the required values of `input` will be communicated from the rank that owns them. In this example, rank 1 will send `input(4)` to rank 0 and `input(7)` to rank 2 (and receive from both ranks 0 and 2 as well). The communication is illustrated in Figure 3.1.

The region required but not owned is usually termed the *ghost zone* (see e.g. [24]), and the process of exchanging data is called *border exchange* or *boundary ex-*



	Rank 0	Rank 1	Rank 2
f.x	0-3	4-7	8-9
input owned	0-3	4-7	8-9
input required	0-4	3-8	7-9

Table 3.1: Owned and required regions of the input buffer for the one-dimensional blur pipeline.

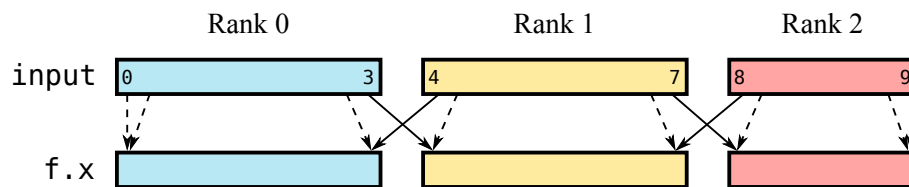


Figure 3.1: Communication for 1D blur. Dotted lines represent on-node access, solid lines represent communication.

*change.* In distributed Halide, ghost zones are automatically inferred by the compiler based on the schedule, and the communication code is inserted automatically. The mechanics of how the ghost zones are calculated and communicated are detailed in Chapter 4.

The importance of performing border exchange can be seen in Figures 3.2 and 3.3. In the first example, the input image in Figure 3.2a was run through the Sobel edge-detection benchmark program, yielding the output in Figure 3.2b. The output in Figure 3.2c is from running the benchmark distributed across 4 nodes with border exchange disabled; clear seams are visible at the edge of each node’s owned region. While the error in this output may be tolerable depending on the particular application of the algorithm, a more extreme example is shown in Figure 3.3. The input image in Figure 3.3a was run through the local Laplacian

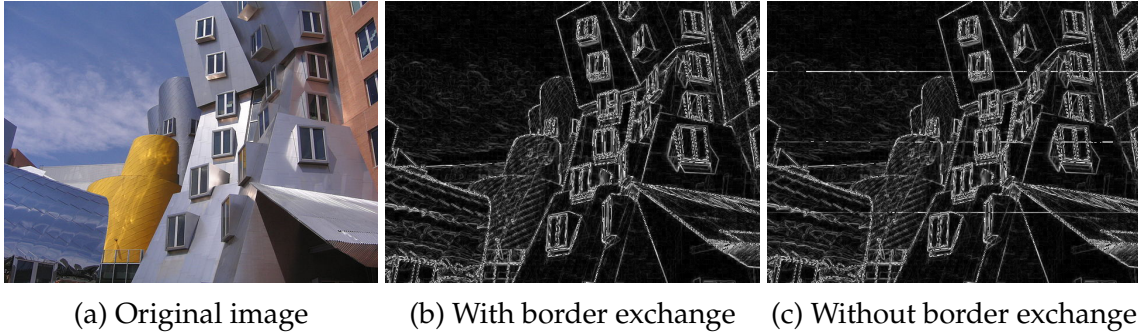


Figure 3.2: Visual impact of border exchange on 4 nodes.

benchmark program, yielding the output image in Figure 3.3b. When distributing on 16 nodes without border exchange, the output is completely garbled, as shown in Figure 3.3c.

This introductory example described a single-stage pipeline. In a multistage pipeline, data must be communicated between the stages. Between each distributed producer and consumer, ghost zones are determined and communication code is automatically inserted by the compiler, just as the case above of communicating `input` to the ranks computing `f`.

### 3.4 Recomputation versus Communication

A fundamental tradeoff exposed by the new scheduling directives `distribute()` and `compute_rank()` is *recomputation versus communication*. In some cases, it may be advantageous to locally recompute data in the ghost zone, instead of communicating it explicitly from the rank that owns the data. While there are models

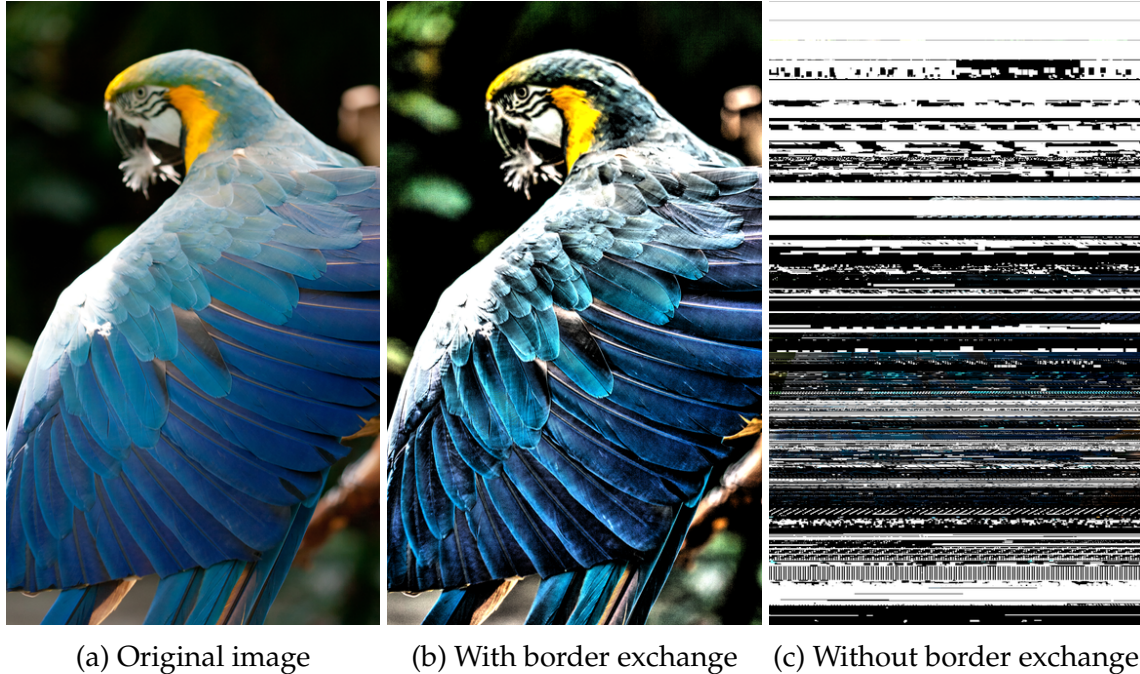


Figure 3.3: Visual impact of border exchange on 16 nodes.

of distributed computation and communication (e.g. [8]) that can be applied to make one choice over the other, these models are necessarily approximations of the real world. For optimal performance, this choice should be made empirically on a per-application basis. With distributed Halide, we can explore the tradeoff not just per application, but per stage in an image processing pipeline.

In distributed Halide, there are three points on the spectrum of this tradeoff. Globally and locally non-redundant work is expressed by the `compute_root()` and `distribute()` directives, ensuring the function is computed exactly once by a single rank for a given point in the function's domain. This is the typical case,

### 3.4. Recomputation versus Communication

Global Redundant	Local Redundant	Communication	Schedule
✓	✓	×	<code>compute_at</code>
✓	×	×	<code>compute_rank</code>
×	×	✓	<code>compute_root</code>

Table 3.2: Points in the redundant computation versus communication tradeoff space.

but communication may be required for consumers of a pipeline stage distributed in this manner. Globally redundant but locally non-redundant work is expressed by the new `compute_rank()` directive, meaning a given point in the function domain may be computed by multiple ranks, but on each rank it is only ever computed once. No communication is required in this case, as each rank computes all of the data it will need for the function’s consumers. Finally, globally and locally redundant work is expressed by scheduling a function `compute_at` inside of its distributed consumer. A given point in the function domain may be computed multiple times within a single rank as well as across ranks, but no communication is required.

Table 3.2 summarizes the tradeoff space of redundant computation versus communication exposed by the new scheduling directives. No one point on this tradeoff spectrum is most efficient for all applications. Distributed Halide exposes this tradeoff to the user, allowing the best choice to be made on a case-by-case basis.

Recalling the  $3 \times 3$  box blur example from Chapter 2, this distributed schedule expresses globally and locally redundant computation of `bh`:

### 3.4. Recomputation versus Communication

---

```
bh.compute_at(bv, y);  
bv.parallel(y).distribute(y);
```

Crucially, even though the pipeline is distributed, *there is no communication of bh*, but instead each rank computes the region of bh it needs for each of the rows it produces in bv. Because the computation of bh occurs within the distributed dimension bv.y, each rank computes bh separately. This means the overlapping rows of bh that are required for each iteration of bv.y are computed redundantly and locally. Communication is still required for the region of the input buffer needed to compute the local portion of bv, but no communication is required for the bh stage.

An alternative schedule that contains no redundant computation, but requires communication of both the input buffer and the bh stage is:

```
bh.compute_root().distribute(y);  
bv.parallel(y).distribute(y);
```

The horizontal blur is computed entirely before the vertical blur begins. Before computing bh, the ghost zone data (required but not owned data) of the input buffer must be communicated between ranks. Then, the overlapping rows of bh.y in the ghost zone must be communicated before computation of bv can begin. This is a case where there is no redundant computation (all pixels of bh are computed exactly once globally).

A more extreme version of redundant computation is the following:

### 3.4. Recomputation versus Communication

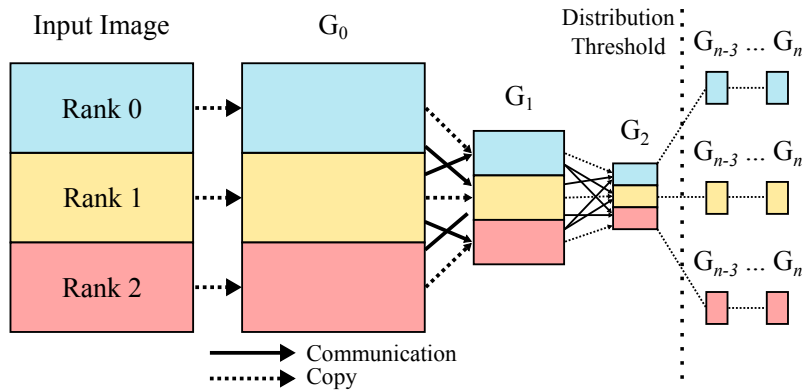


Figure 3.4: Communication for the Gaussian pyramid computation in the Local Laplacian benchmark. The final three levels after the “distribution threshold” are redundantly computed by every rank.

```
bh.compute_root();  
bv.parallel(y).distribute(y);
```

With this schedule, the entire horizontal blur (i.e. over the entire global input image) is evaluated on every rank. This is wasteful in terms of computation, as each rank will compute more of `bh` than it needs. However, *locally* there is no redundant computation, and globally there is no communication required for `bh`. Using this particular strategy is crucial for scalability on the local Laplacian benchmark, as shown in Figure 3.4. The final three stages of the image pyramid in Figure 3.4 are recomputed on every node, as the data is small enough that recomputation is faster than communication.

Finally, this schedule express globally redundant but locally non-redundant computation:

```
bh.compute_rank();
```

```
bv.parallel(y).distribute(y);
```

Each rank will non-redundantly (i.e. at root level on each rank) compute only the region of `bh` required to compute the local portion of `bv`. No communication is required in this case. However, neighboring ranks will compute overlapping rows of `bh`, meaning globally there is some redundant computation.

## 3.5 On-Node Scheduling

The new `distribute()` and `compute_rank()` directives compose with existing Halide scheduling directives. All ranks inherit the same schedule for computing the local portion of a global computation (typically referred to as the *single program, multiple data* or SPMD pattern). To express the common idiom of distributing data across ranks and locally parallelizing the computation on each rank, the `parallel()` directive can be used in conjunction with the new `distribute()` directive. The various existing scheduling directives, modulo several current limitations, can be composed arbitrarily to arrive at complex schedules of computation and communication. For example, the following schedule taken from the block transpose benchmark causes `f` to be computed by locally splitting the image into  $16 \times 16$  tiles, vectorizing and unrolling the computation of each tile, distributing the rows of `f` and locally parallelizing over the rows of tiles:

```
f.tile(x, y, xi, yi, 16, 16)
    .vectorize(xi).unroll(yi)
    .parallel(y).distribute(y);
```

The flexibility of this approach allows programmers to specify efficient on-node schedules and freely distribute the computation of each stage, without worrying about calculating ghost zones or writing communication code.

## 3.6 Limitations

The current implementation of distributed Halide supports all of the features described above, but there are several engineering challenges remaining to be addressed. In particular, ahead of time compilation has not yet been implemented; currently only JITted pipelines can be distributed. Only dimensions that can be parallelized can be distributed, i.e. distributing data-dependent dimensions (as used in a histogram, for example) is unimplemented. Nested distributions with a parametric processor grid are not yet supported, as previously mentioned in Section 3.2. Any stage writing to a distributed output buffer must currently have the same distribution as the output buffer. Reordering storage with the `reorder_storage()` scheduling directive is not yet supported for distributed dimensions.



# Chapter 4

## Code Generation

This section details the new analysis and lowering passes added to the Halide compiler to generate code for distributed pipelines. There are two components of code generation: determining ghost zones for each distributed producer-consumer relationship in the pipeline, and generating MPI calls to communicate required data in the ghost zones. The mechanisms presented here are similar to those in previous work such as [16] for affine loop nests; see Chapter 6 for a discussion of their work. The main advantage of this approach lies in the simplicity of ghost zone inference and code generation. We can generate efficient communication code with these simple mechanisms due to the additional domain-specific knowledge about the pipeline available to the Halide compiler.

## 4.1 Ghost Zone Inference

Ghost zone inference relies heavily on the axis-aligned bounding box bounds inference already present in the Halide compiler. In regular Halide, bounds information is needed to determine allocation sizes of intermediate temporary memory, iteration spaces of pipeline stages and out-of-bounds checks, among other things. We use the bounds inference subsystem to construct both a global and local picture of the regions of buffers belonging to each rank.

For each consumer stage in the pipeline, we generate the owned and required information for its inputs, which may be `DistributedImages` or earlier stages in the pipeline. We derive the owned and required regions in terms of the global buffer bounds the programmer provides via the `DistributedImage` type. All derived bounds throughout the pipeline will be in terms of these global sizes.

Recall the iteration space slicing from Section 3.2 and the one-dimensional blur  $\mathbb{f}$  from Section 3.3. Applying bounds inference to the distributed loop nest generates the symbolic owned and required regions for computing  $\mathbb{f}$  (omitting boundary conditions for simplicity):

	Rank $r$
$\mathbb{f}.x$	$rs$ to $(r+1)s$
input owned	$rs$ to $(r+1)s$
input required	$rs - 1$ to $(r+1)s + 1$

Identical inference is done for every producer-consumer in the distributed pipeline. Multidimensional buffers are handled with the same code: the bounds inference information generalizes across arbitrary dimensions, including nested distribution of dimensions.

Because these regions are parameterized by a rank variable, any particular rank  $r$  can determine the owned and required regions for another rank  $r'$ . A global mapping of rank to owned region is never explicitly computed or stored; instead it is computed dynamically when needed. By computing data locations lazily, we avoid creating and accessing a mapping of global problem space to compute rank.

Border exchange is required for the distributed inputs of each consumer in the pipeline. The inputs could be `DistributedImages` or earlier distributed stages in the pipeline. In the following discussion we will refer to these collectively as “data sources,” as the owned and required regions are computed the same way no matter the type of input.

To perform a border exchange for data source  $b$  between two ranks  $r$  and  $r'$ , each must send data it owns to the other rank if it requires it. Let  $H(b;r)$  be the owned (or “have”) region of data source  $b$  by rank  $r$  and let  $N(b;r)$  be the required (or “need”) region. If  $H(b;r)$  intersects  $N(b;r')$ , rank  $r$  owns data required by  $r'$ , and symmetric send/receive calls must be made on each rank.

The  $H$  and  $N$  regions are represented by multidimensional axis-aligned bounding boxes, where each dimension has a minimum and maximum value. Com-

puting the intersection  $I$  of the two bounding boxes is done using the following equations:

$$I_d(b, r, r').\text{min} = \max\{H_d(b; r).\text{min}, N_d(b; r').\text{min}\}$$

$$I_d(b, r, r').\text{max} = \min\{H_d(b; r).\text{max}, N_d(b; r').\text{max}\}$$

where  $B_d(\cdot).\text{min}/\text{max}$  denotes the minimum or maximum in dimension  $d$  of bounding box  $B$ . Applying to the one-dimensional blur yields:

Region	Value
$H(\text{input}; r)$	$rs$ to $(r + 1)s$
$N(\text{input}; r')$	$r's - 1$ to $(r' + 1)s + 1$
$I(\text{input}, r, r')$	$\max\{rs, r's - 1\}$ to $\min\{(r + 1)s, (r' + 1)s + 1\}$

We generate the communication code using this static representation of the intersection between what a rank  $r$  has and what a rank  $r'$  needs.

The intersections are calculated using global coordinates (relative to the global input and output buffer extents). The actual buffers allocated on each rank are only the size of the local region. Thus, before passing the intersection regions to the MPI library, they must be converted to local coordinates, offset from 0 instead of  $rs$ . For rank  $r$  and a region  $X$  of data source  $b$  in global coordinates, define  $L(X, b; r)$  to be  $X$  in coordinates local to rank  $r$ .  $L$  is computed by subtracting the

global minimum from the global offset to compute a local offset:

$$L_d(X, b; r).min = X_d.min - H_d(b; r).min$$

$$L_d(X, b; r).max = X_d.max - H_d(b; r).min.$$

## 4.2 Communication Code Generation

Preceding each consumer stage in the pipeline, we inject MPI calls to communicate the ghost zone region of all distributed inputs required by the stage. This process is called the border exchange.

Recall the distributed one-dimensional blur from Section 3.3. As was illustrated in Table 3.1, the owned region of buffer `input` is smaller than the required region. Thus, we must perform a border exchange on the `input` buffer as was depicted in Figure 3.1. An initial lowering pass converts the loop nest for `f` into a distributed loop nest by slicing the iteration space:

```
let R = mpi_num_ranks()
let r = mpi_rank()
let s = ceil(w/R)
for x from r*s to min(w-1, (r+1)*s):
    f[x] = (input[x-1] + input[x+1]) / 2
```

The number of ranks `R` and the current rank `r` are symbolic values determined at runtime by calls to MPI. Keeping these values symbolic means that the bounds inference applied to this loop nest will be in terms of these symbols. This allows us to not require recompilation when changing the number of ranks.

Generating the code to perform border exchange uses the inferred symbolic ghost zone information. For a data source `b`, the function `border_exchange(b)` is generated with the following body:

```
function border_exchange(b) :
  let R = mpi_num_ranks()
  let r = mpi_rank()
  for r' from 0 to R-1:
    // What r has and r' needs:
    let I = intersect(H(b,r), N(b,r'))
    // What r needs and r' has:
    let J = intersect(H(b,r'), N(b,r))
    if J is not empty:
      let LJ = local(J, b, r)
      mpi_irecv(region LJ of b from r')
    if I is not empty:
      let LI = local(I, b, r)
      mpi_isend(region LI of b to r')
  mpi_waitall()
```

Inserting a call to the border exchange before computation begins completes the code generation process:

```
let R = mpi_num_ranks()
let r = mpi_rank()
let s = ceil(w/R)
border_exchange(input)
for x from r*s to min(w-1, (r+1)*s):
  f[x] = (input[x-1] + input[x+1]) / 2
```

In the border exchange algorithm the `i` prefix on `isend` and `irecv` denotes the non-blocking version of that communication function. Using non-blocking calls allows the communication of multiple buffers to overlap. Additionally, this strategy avoids potential deadlocks on resource availability (e.g. memory for MPI to allocate communication buffers it needs). All of the outstanding communication requests will be queued until resources become freed by the completion of a previous request.

Performing border exchanges for multidimensional buffers requires more specialized handling. In particular, the regions of multidimensional buffers being communicated may not be contiguous in memory. We handle this case using MPI derived datatypes, which allow a non-contiguous region of memory to be sent or received with a single MPI call. The MPI implementation automatically performs the packing and unpacking of the non-contiguous region, as well as allocation of scratch memory as needed.

Due to the parameterization with the number of ranks, the precise shape of the region being sent is not known at compile time. Thus, we must also generate code to create and commit the MPI derived datatypes at runtime. Each call to `mpi_irecv` or `mpi_isend` in the border exchange first goes through a thin wrapper function implemented in the Halide runtime. Before the call to this wrapper function, code is generated to calculate the size and byte offset of the region being communicated. This is straightforward to calculate given the bounding box information discussed in the previous section. The wrapper functions

use these values to construct an MPI subarray datatype, which is then committed via `MPI_Type_commit`. These committed types are pushed to a small queue so that they may be freed by the runtime once they are no longer needed (after the termination of the `waitall()` MPI call).

The ability to use derived datatypes for communicating non-contiguous data, along with wide support on a variety of popular distributed architectures, was among the reasons we chose to use MPI as the target of our code generation.

## 4.3 Rank Iteration Space

The border exchange algorithm could be improved using additional domain knowledge available to the Halide compiler, namely the footprint sizes of each stage in the pipeline. Using this information can, in some cases, allow the communication loop to only iterate over a subset instead of all ranks. This would lead to better scaling behavior with large numbers of ranks. While not yet implemented, this section discusses an algorithm that could be used to implement this optimization. All of the experimental results in Chapter 5 were measured without this optimization in place.

Consider again the one-dimensional blur example stencil:

$$f(x) = (\text{input}(x - 1) + \text{input}(x + 1)) / 2;$$

Suppose that both stage `f` and `DistributedImage input` were distributed along `x`. In this example, when communicating the required region  $N(\text{input}; r)$



for to rank  $r$ , it suffices to communicate only with rank  $r - 1$  and  $r + 1$ , due to the shape (or “footprint”) of the  $\mathfrak{f}$  stencil. In other words, ranks beyond a radius of 1 do not have `input` data needed to compute  $\mathfrak{f}$  on rank  $r$ . Let  $k$  be that rank radius required for communication. Using the statically-available footprint size of the  $\mathfrak{f}$  stencil, a value for  $k$  can be determined at compile time. In general, the rank radius is dependent on the particular data source being communicated as well as the particular stage consuming it, i.e. let  $K(f, b)$  be the rank radius for communicating data source  $b$  for consumer stage  $f$ .

Let  $F(f, b, d)$  be the footprint size of consumer stencil  $f$  for data source  $b$  along dimension  $d$ , and let  $F^*(f, b)$  be the maximum footprint size across all dimensions, i.e.

$$F^*(f, b) = \max_d F(f, b, d).$$

Let  $E(b, d)$  be the extent of data source  $b$  in dimension  $d$ . In the case where  $d$  is distributed, this is equal to the global extent of  $d$  divided by the number of ranks  $R$ . Then let  $E^*(b)$  be the minimum extent across all dimensions of  $b$ :

$$E^*(b) = \min_d E(b, d).$$

Then

$$K(f, b) = \left\lceil \frac{F^*(f, b)}{E^*(b)} \right\rceil.$$

The footprint  $F^*$  cannot be used directly as the rank radius  $K$ . This is because  $K$  also depends on the ownership of the data source  $b$ . For example, a footprint size of 4 may have a rank radius of 1 if the extent of  $b$  on each rank is  $\geq 4$ .

However, if each rank owns  $\leq 4$  of  $b$ , then a footprint of 4 must communicate with a greater radius than just 1.

When the extents of a data source are explicitly known at compile time, both the  $F^*$  and  $E^*$  functions can be statically evaluated. Otherwise, symbolic expressions can be generated for these functions to compute a value of  $K$  at runtime.

This optimization can only be performed when footprint sizes are fixed and known statically. Notably, this excludes the optimization from being applied in cases with input-dependent stencils such as in the computation of a histogram, or reduction domain over an entire data source.

# Chapter 5

## Evaluation

We evaluated distributed Halide by taking nine existing image processing benchmarks written in Halide and distributing them using the new scheduling directives and the new data type `DistributedImage`. The benchmarks range in complexity from the simple two-stage box blur to an implementation of a local Laplacian filter with 99 stages. For each, we began with the single-node schedule tuned by the author of the benchmark. All schedules were parallelized, and usually used some combination of vectorization, loop unrolling, tiling and various other optimizations to achieve excellent single-node performance. We then modified the schedules to use the distributed Halide extensions. Many of the benchmarks are the same as in the original Halide work [31]. A brief description of each benchmark follows.

---

**Bilateral grid** This filter blurs the input image while preserving edges [13]. It consists of a sequence of three-dimensional blurs over each dimension of the input image, a histogram calculation and a linear interpolation over the blurred results.

**Blur** An implementation of the simple 2D 9-point box blur filter as two separable 3-point stencil stages.

**Camera pipe** An implementation of a pipeline used in digital cameras, which transforms the raw data collected by the image sensors into a usable digital image. This pipeline contains more than 20 interleaved stages of interpolation, demosaicing, and color correction, and transforms a two-dimensional input into a three-dimensional output image.

**Interpolate** A multi-scale image pyramid [7] is used to interpolate an input image at many different resolutions. The image pyramid consists of 10 levels of inter-dependent upsampling and downsampling and interpolation between the two.

**Local Laplacian** This filter [29] performs a complex edge-preserving contrast and tone adjustment using an image pyramid approach. The pipeline contains 99 stages and consists of multiple 10-level image pyramids including a Gaussian pyramid and Laplacian pyramid. Between each stage are complex and data-

---

dependent interactions, leading to an incredibly large schedule space. This is our most complex benchmark.

**Resize** This filter implements a 130% resize of the input image using cubic interpolation, consisting of two separable stages.

**Sobel** An implementation of image edge-detection using the well-known Sobel kernel.

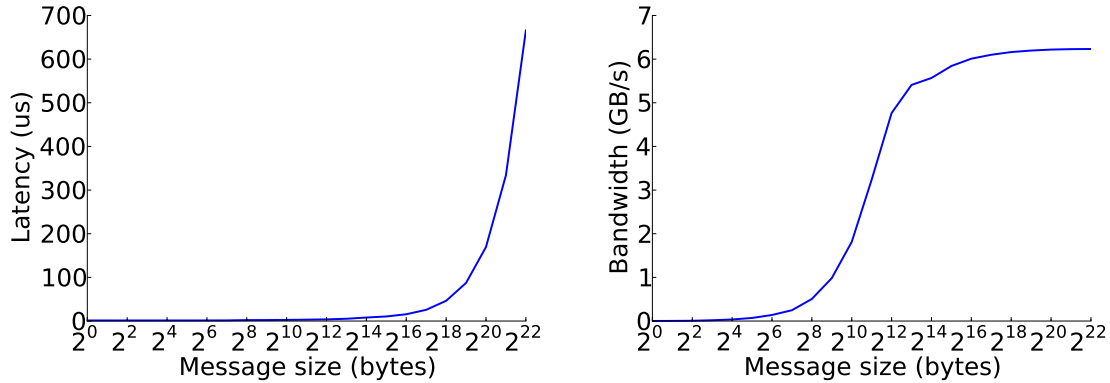
**Transpose** An implementation of a blocked image transpose algorithm.

**Wavelet** A Daubechies wavelet computation.

The testing environment was a 16 node Intel Xeon E5-2695 v2 @ 2.40GHz Infiniband cluster with Ubuntu Linux 14.04 and kernel version 3.13.0-53. Each node had two sockets, and each socket had 12 cores, for a total of 384 cores. Hyperthreading was enabled, and the Halide parallel runtime was configured to use as many worker threads as logical cores. The network topology was fully connected.

To analyze the network performance of the test machine we ran the Ohio State microbenchmark suite [28]. The point-to-point MPI latency and effective bandwidth measurements are reported in Figures 5.1a and 5.1b respectively.

Due to the presence of hyperthreading and the dynamic load balancing performed by the Halide parallel runtime, the performance numbers had nonnegli-



(a) Point-to-point latency

(b) Point-to-point bandwidth

Figure 5.1: Network point-to-point latency and bandwidth measurements for our testing environment.

gible noise. As the input size decreases for a multithreaded Halide pipeline, the variance in runtime increases. For a  $1000 \times 1000$  parallel blur with unmodified Halide, over 1,000 iterations we recorded a standard deviation of 21.3% of the arithmetic mean runtime. At  $23,000 \times 23,000$ , we recorded a standard deviation of 2.1%. In a distributed pipeline, even though the global input may be large enough to lower the variance, each rank has a smaller region of input and therefore higher variance. To mitigate this variance as much as possible in our measurements of distributed Halide, we take median values of 50 iterations across for each node and report the maximum recorded median. The timing results were taken using `clock_gettime(CLOCK_MONOTONIC)`, a timer available on Linux with nanosecond resolution.

We first compare two benchmarks to popular open-source optimized versions

to illustrate the utility of parallelizing these benchmarks, even at small input sizes. We then report performance of distributed Halide in two categories: scaling and on-node speedup.

### 5.1 OpenCV Comparison

To establish the utility of using Halide to parallelize and distribute these benchmarks, we first compare against reference sequential implementations of the box blur and edge-detection benchmarks. We chose to compare against OpenCV [5], a widely-used open source collection of many classical and contemporary computer vision and image processing algorithms. The OpenCV implementations have been hand-optimized by experts over the almost 20 years it has been in development.

We chose box blur and edge-detection to compare because OpenCV contains optimized serial implementations of both kernels, whereas both Halide benchmarks are fully parallelized. We built OpenCV on the test machine using the highest vectorization settings (AVX) defined by its build system. The results are summarized in Tables 5.1 and 5.2. For the largest tested input size, the parallel single-node Halide implementation was  $8.5\times$  faster for box blur and  $11\times$  faster for Sobel. Even for these simple pipelines there is a need for parallelism.

<b>Input Size</b>	<b>Distr. Halide (s)</b>	<b>OpenCV (s)</b>	<b>Speedup</b>
1000 × 1000	0.002	0.002	1.0×
2000 × 2000	0.002	0.009	1.255×
4000 × 4000	0.004	0.033	8.252×
10000 × 10000	0.023	0.223	9.697×
20000 × 20000	0.096	0.917	9.552×
50000 × 50000	0.688	5.895	8.568×

Table 5.1: Speedup of Distributed Halide box blur over OpenCV.

<b>Input Size</b>	<b>Distr. Halide (s)</b>	<b>OpenCV (s)</b>	<b>Speedup</b>
1000 × 1000	0.003	0.004	1.020×
2000 × 2000	0.004	0.019	4.752×
4000 × 4000	0.010	0.074	7.4×
10000 × 10000	0.054	0.446	8.259×
20000 × 20000	0.183	1.814	9.913×
50000 × 50000	1.152	12.674	11.001×

Table 5.2: Speedup of Distributed Halide Sobel edge detection over OpenCV.

## 5.2 Scaling

To test the scalability of distributed Halide, we ran each benchmark on increasing numbers of ranks with a fixed input size. Then, we repeated the scaling experiments with several input sizes up to a maximum value. These results measure the benefit of distributed computation when the communication overhead is outstripped by the performance gained from increased parallelism.

As a baseline, for each benchmark and input size, we ran the non-distributed version on a single node. As mentioned previously, the parallel runtime was con-



figured to use as many threads as logical cores. Therefore, for all benchmarks we normalized to the non-distributed, single-node, 24-core/48-thread median runtime on the given input size.

When increasing the number of nodes, we adopted a strategy of allocating two ranks per node. This maximized our distributed performance by mitigating effects of the NUMA architecture, explored in more detail in the following section.

Scaling results from all nine benchmarks are presented in Figure 5.2. Broadly speaking, the results fall into three categories.

In the first category are the bilateral grid, blur, resize, Sobel, transpose and wavelet benchmarks. This category represents benchmarks exhibiting predictable and well-scaling results. The distribution strategy in bilateral grid, blur and wavelet was the same, utilizing multiple stages with redundant computation. The only data source requiring communication for these benchmarks was the input buffer itself: once the (relatively small) input ghost zones were received, each rank could proceed independently, maximizing parallel efficiency. On bilateral grid, even the smallest input size achieved a  $8.8\times$  speedup on 16 nodes, with the maximum input size achieving  $12.1\times$  speedup. On blur and wavelet, the smallest input size achieved a speedup only around  $4\times$ : both blur and wavelet have very low arithmetic complexity, meaning with small input sizes each rank was doing very little computation.

Transpose, which belongs to the first category, demonstrated good scaling

## 5.2. Scaling

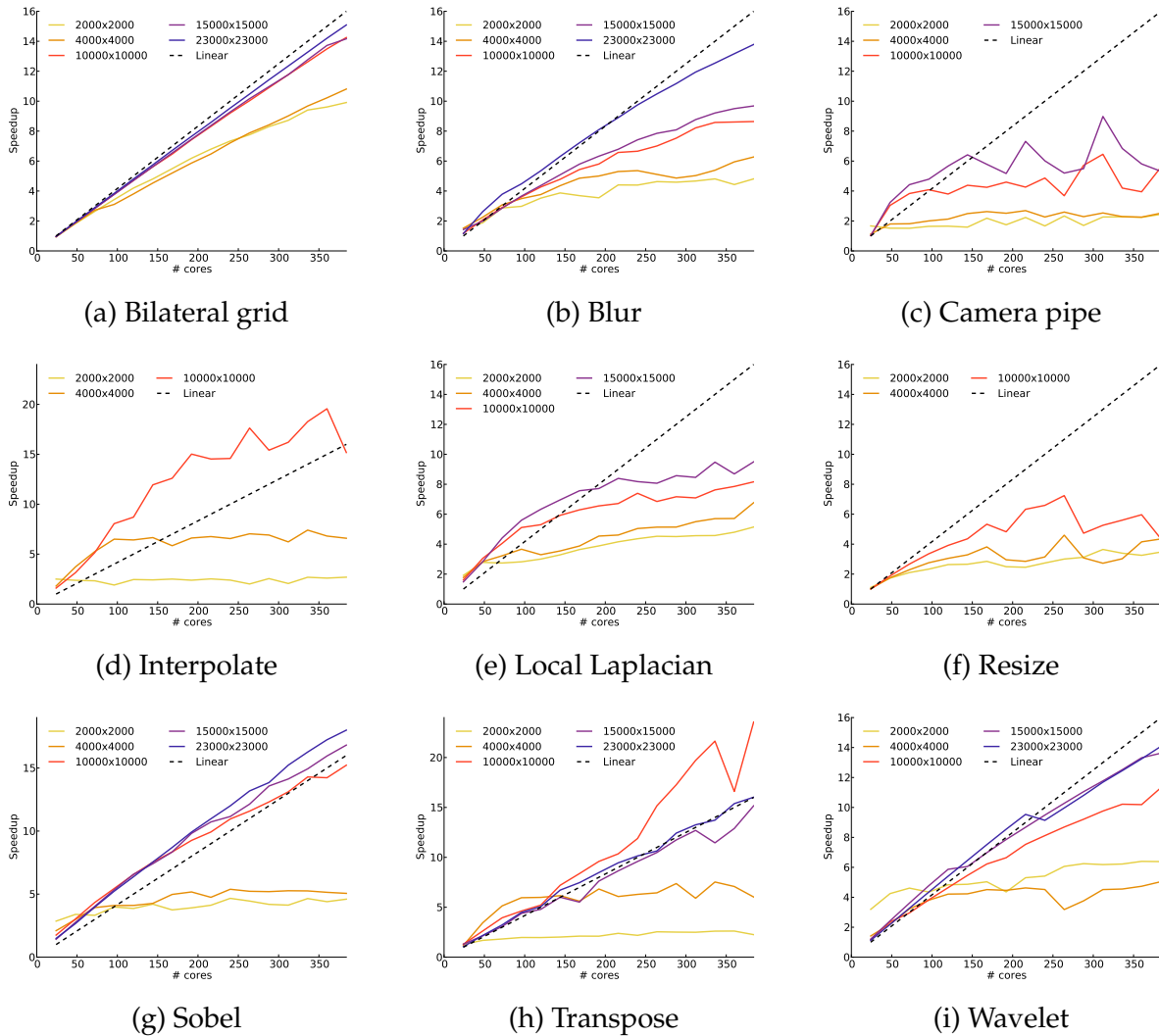


Figure 5.2: Scaling results across all benchmarks with varying input sizes.

when distributing the input and output buffers along opposite dimensions. We distributed the input along the x dimension and output along the y dimension, requiring only on-node data access to perform the transpose. If we distributed

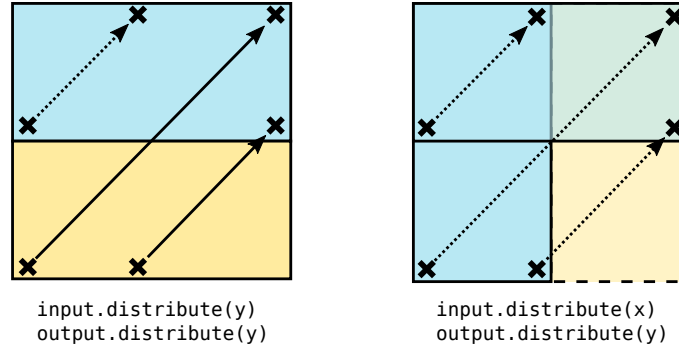


Figure 5.3: Two data distributions in transpose. By distributing the input along the opposite dimension as the output, only local accesses (dotted lines) are required to transpose the input, as opposed to the explicit communication (solid lines) in the other case.

# nodes	Input Distr.	Runtime (s)	Speedup
1	N/A	0.119	1.0 ×
16	y	0.067	1.779 ×
16	x	0.007	16.172 ×

Table 5.3: Speedup of transpose on  $23000 \times 23000$  image with different input distributions.

both the input and output along the same dimension, the ghost zone for the input on each rank would have required communication. These two strategies are visualized in Figure 5.3. In Table 5.3 we compare the speedup of transpose with 16 nodes using each data distribution. The difference between the two data distributions is an order of magnitude of speedup gained.

The second category consists of camera pipe and local Laplacian. These benchmarks exhibit less scalability than those in the first category. Both the camera pipe and local Laplacian pipelines are complex, leading to a large schedule space,

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and we expect that by exploring further schedules, even better scalability can be achieved. Regardless of their suboptimal schedules, local Laplacian and camera pipe achieved a  $7.7\times$  and  $11.2\times$  speedup on 16 nodes, respectively, for their largest input sizes.

The final category consists of interpolate. This benchmark displayed super-linear scaling for larger input sizes. The image-pyramid based interpolation displayed some of the best scaling behavior, even at a maximum input size of  $20,000\times 20,000$ . We accomplished this in part by utilizing redundant computation in the later stages of the pyramid, using the strategy visualized in Figure 3.4. In addition, the distributed pipeline exhibits better hardware utilization: as the working set size decreases per rank, each processor can make more effective use of its cache, leading to better memory bandwidth utilization. Finally, NUMA-aware data partitioning leads to better on-node parallel efficiency, and is explored in more detail in the following subsection.

To measure an estimation of scaling efficiency, we also measured the communication overhead for each benchmark on the smallest input and a mid-range input size ( $1000 \times 1000$  and  $20000 \times 20000$  respectively), on a single node (with two MPI ranks) and 16 nodes (with 32 MPI ranks, one per socket). We used the MPIP [34] library to gather these results over all iterations. The results are summarized in Table 5.4. The “1k/1N” column refers to the input size of 1,000 on 1 node; similarly for the other columns. The “App” and “MPI%” columns refer to the aggregate application execution time in seconds and the percentage of that

Benchmark	1k/1N		1k/16N		20k/1N		20k/16N	
	App. (s)	MPI%	App.	MPI%	App.	MPI%	App.	MPI%
bilateral grid	2.43	0.04	9.83	53.65	809	0.08	847	2.47
blur	0.19	14.16	5.87	93.46	16.4	0.82	28.8	12.93
camera pipe	0.86	13.24	–	–	78.5	0.42	140	28.24
interpolate	1.27	22.64	23.6	68.31	188	3.64	250	44.05
local laplacian	3.07	10.5	30.6	61.83	360	6.42	813	72.26
resize	0.6	7.61	3.96	71.45	59.3	1.42	131	42.09
sobel	0.13	12.32	7.16	92.93	18.6	1.22	30.7	23.41
transpose	0.09	7.58	1.01	69.66	9.83	0.10	14.7	39.84
wavelet	0.20	10.81	2.05	66.15	13	0.67	20.9	27.52

Table 5.4: Communication and computation time for each benchmark.

time spent in the MPI library. Roughly speaking, the benchmarks which exhibit poor scaling (the second category) have a larger fraction of their execution time consumed by communication; for example, nearly 75% of the execution time of local Laplacian across 16 nodes is spent communicating or otherwise in the MPI library. This indicates that the distributed schedules for these benchmarks are not ideal. Further experimentation with distributed scheduling would likely lead to improved scalability on these benchmarks. We were unable to run the 1k/16N case for camera pipe because this benchmark contains a distributed dimension of only extent 30 with an input size of 1,000, which cannot be distributed across 32 ranks.

## 5.3 On-Node Speedup from NUMA-Aware Distribution

### Distribution

To quantify the portion of speedup seen with “distributing” a Halide pipeline on a single node, we used the open-source Intel PMU profiling tools [6]. These expose a wider range of symbolic hardware performance counters than is readily available in the standard Linux `perf` tool. For this experiment, we ran a  $23,000 \times 23,000$  2D box blur under different NUMA configurations. During each run we gathered several performance counters for LLC (last level cache) misses satisfied by relevant sources. In particular we looked at:

- LLC demand read misses, any resolution  
(`offcore_response_demand_data_rd_llc_miss_any_response`)
- LLC demand read misses resolved by local DRAM  
(`offcore_response_demand_data_rd_llc_miss_local_dram`)
- LLC demand read misses resolved by remote DRAM  
(`offcore_response_demand_data_rd_llc_miss_remote_dram`)

Demand misses in this context refer to misses that were not generated by the prefetcher. We also measured misses resolved by hits in remote L2 cache, but these amounted to less than 0.1% of the total misses, so are not reported here.

### 5.3. On-Node Speedup from NUMA-Aware Distribution

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We gathered these performance counters under four NUMA configurations of the 2D blur. In all cases, the schedule we used evaluated rows of the second blur stage in parallel (i.e. `blur_y.parallel(y)`). For the distributed case, we simply distributed along the rows as well, i.e. `blur_y.parallel(y).distribute(y)`.

The four configurations were:

- Halide: Regular multithreaded Halide executing on all 24 cores.
- NUMA Local: Regular Halide executing on 12 cores on socket 0, and memory pinned to socket 0.
- NUMA Remote: Regular Halide executing on 12 cores on socket 0, but memory pinned to socket 1.
- Distr. Halide: Distributed Halide executing on all 24 cores, but with one MPI rank pinned to each socket.

For the “local” and “remote” NUMA configurations, we used the `numactl` tool to specify which cores and sockets to use for execution and memory allocation. The “local” NUMA configuration is invoked with `numactl -m 0 -C 0-11,24-35`, specifying that memory should be allocated on socket 0, but only cores 0-11 (and hyperthread logical cores 24-35) on socket 0 should be used for execution. The “remote” configuration used `numactl -m 1 -C 0-11,24-35`.

The results of these four scenarios are summarized in Table 5.5. The results indicate that approximately 50% of the last-level cache misses during regular

### 5.3. On-Node Speedup from NUMA-Aware Distribution

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multithreaded Halide execution required a fetch from remote DRAM. By using distributed Halide to pin one rank to each socket (the “distributed Halide” configuration), we achieve near-optimal NUMA performance, where 99.5% of LLC misses were able to be satisfied from local DRAM.

Another item of note in the Table 5.5 is the total number of LLC misses from regular to distributed Halide in this scenario. This is due to the partially static, partially dynamic scheduling that occurs with the distributed schedule. In effect, each rank is statically responsible for the top or bottom half of the rows of the input. Then, parallelization using the dynamic scheduling happens locally over each half. Restricting the domain of parallelism results in better cache utilization on each socket, meaning many of the accesses that missed LLC in regular Halide become hits in higher levels of cache with distributed Halide.

Table 5.6 summarizes the benefit of using a distributed pipeline to form NUMA-aware static partitions. For each benchmark, we report the runtime of the maximum input size of the regular Halide pipeline versus the distributed pipeline. The distributed pipeline was run on a single node with the same number of cores, but one rank was assigned to each of the two sockets. The numbers are the median runtimes of 50 iterations.

While taking advantage of NUMA could also be done in the parallel runtime, our approach allows the distributed scheduling to generalize to handle NUMA-aware static scheduling, while maintaining the dynamic load balancing already present. This fits within the general Halide philosophy of exposing choices like



Config	Total # Misses	% Local DRAM	% Remote DRAM
Halide	$3.85 \times 10^9$	51.5%	48.5%
NUMA Local	$2.36 \times 10^9$	99.6%	0.4%
NUMA Remote	$3.48 \times 10^9$	3.6%	96.4%
Distr. Halide	$2.29 \times 10^9$	99.5%	0.5%

Table 5.5: LLC miss resolutions during  $23,000 \times 23,000$  blur under several NUMA configurations.

Benchmark	Halide (s)	Distr. Halide (s)	Speedup
bilateral grid	9.772	10.116	$0.966 \times$
blur	0.657	0.585	$1.122 \times$
camera pipe	4.081	4.889	$0.834 \times$
interpolate	2.588	1.822	$1.420 \times$
local laplacian	11.826	10.003	$1.182 \times$
resize	3.712	3.076	$1.206 \times$
sobel	1.104	1.172	$0.941 \times$
transpose	0.641	0.610	$1.050 \times$
wavelet	0.673	0.712	$0.944 \times$

Table 5.6: Runtime and speedup on a single node and the same number of cores with NUMA-aware distribution over two ranks, using each benchmark’s maximum sized input.

these as scheduling directives: in effect, the `distribute()` directive can also become a directive for controlling NUMA-aware partitioning of computation.

## 5.4 Scalability on Cori

In order to support next-generation large-scale image processing, it is necessary for distributed Halide to scale to much higher core counts, such as what would

used on supercomputer scale problems. Our testbed machine configuration is not quite representative of typical supercomputer architectures, not least due to the fact that our test network topology is fully connected. To measure how well our results generalize to a real supercomputer, we repeated the scalability measurements on “Cori,” the newest supercomputer available at NERSC [3].

Cori is a Cray XC40 supercomputer, with a theoretical peak performance of 1.92 Petaflops per second. It has 1,630 compute nodes totaling 52,160 cores. Each compute node has two sockets, each of which is Intel Xeon E5-2698 v3 @ 2.3GHz. The network infrastructure is Cray Aries, with the “Dragonfly” topology. Each node has 128GB of main memory. More details can be found at [3]. We ran our scalability tests up to a total of 64 nodes, or 2,048 cores.

The findings are summarized in Figure 5.4. The scalability of the benchmarks is similar to those observed on our testing machine. On 64 nodes, the blur benchmark achieves a  $57\times$  speedup for a parallel efficiency of 89%, similar to the 86% efficiency on the 16 node test machine. The benchmarks that exhibited a falloff in scaling on our testing machine (such as local Laplacian) unsurprisingly do not scale on Cori. In the case of interpolate and resize, benchmarks that exhibited decent scaling on our testing machine, the falloff in scalability is due to strong scaling. We were unable to measure a single-node baseline for larger input sizes on these two benchmarks due to memory constraints. Thus, the curves quickly fall off as the limits of useful distribution are reached.

The transpose benchmark appears to display an accelerating scaling curve on

smaller inputs, but these results should be taken with a grain of salt. We included small input sizes up to  $20,000 \times 20,000$  for consistency across benchmark results, but the absolute difference in execution time between 32 and 64 nodes (1,024 and 2,048 cores) is less than 0.01 seconds, and the baseline is on the order of 0.1 seconds, as reported in Table 5.6. Thus, the overall effect on execution time is nearly negligible from 32 to 64 nodes.

In general, a larger input size is required to see similar scaling at the 384 core count of our test machine. Most likely this is due to increased network contention during execution. In particular, the compute nodes assigned by the Cori job scheduler are not chosen based on locality, meaning the number of hops required for point-to-point communication can be much larger than on our test machine (which was fully connected). Additionally, Cori is a shared resource, meaning network contention with unrelated jobs could also have a non-negligible impact on scalability of these applications.

## 5.5 Terapixel Results

We evaluated distributed Halide on terapixel-sized inputs ( $10^{12}$  pixels) on two of the image processing benchmarks and one representative simulation benchmark. The two image processing benchmarks, blur and Sobel, were chosen because image smoothing and edge detection are two common tasks for stitching disparate input images into a monolithic output, a typical scenario today at the

terapixel scale. Additionally, because Cori is a shared and accounted resource, long-running large-scale jobs are difficult to schedule; blur and Sobel had the added advantage of a relatively short wallclock execution time. The input size for these benchmarks was  $1,000,000 \times 1,000,000$ .

The simulation benchmark was a simple 3D heat equation solver discretized using the finite difference method, namely the 7-point stencil

$$U_t(x, y, z) = c_0 U_{t-1}(x, y, z) + c_1 (U_{t-1}(x + 1, y, z) + U_{t-1}(x - 1, y, z) + U_{t-1}(x, y + 1, z) + U_{t-1}(x, y - 1, z) + U_{t-1}(x, y, z + 1) + U_{t-1}(x, y, z - 1)).$$

The timings reported for the heat benchmark are for a single timestep of the solver, meaning the scaling can be directly extrapolated for arbitrary numbers of timesteps. The input size for this benchmark was  $10,000 \times 10,000 \times 10,000$ .

The baseline for these benchmarks was the minimum number of Cori nodes with enough aggregate main memory to process the terapixel-sized image. Each benchmark tested used four-byte pixels, leading to a  $4 \times 10^{12} / 2^{40} = 3.64$  terabyte image. Each compute node must have memory enough at least for the input and output image sections; on Cori, each node has roughly 120 GB of usable main memory, leading to a minimum of  $7.28\text{TB} / 0.12\text{TB} = 62$  nodes, which was rounded up to 64.

The results are summarized in Table 5.7. The runtime reported is the median runtime of 50 iterations of the benchmark (an “iteration” in the heat benchmark is

# nodes	Heat		Blur 1D		Blur 2D		Sobel	
	Time (s)	×	Time	×	Time	×	Time	×
*64	5.218	1×	4.628	1×	3.708	1×	7.137	1×
128	2.612	2.0×	2.341	2.0×	1.485	2.5×	3.687	1.9×
256	1.273	4.1×	1.901	2.4×	0.702	5.3×	1.809	3.9×
512	0.627	8.3×	4.233	1.1×	0.335	11.1×	0.905	7.9×

Table 5.7: Scaling results for three benchmarks on terapixel inputs. \*The baseline number of nodes for Blur 2D was 66.

a single timestep). The heat benchmark (using 3D distribution) displays slightly superlinear scaling, a good sign that the hardware is being very well utilized. The Sobel benchmark (using 1D distribution) displays similar scaling as reported in the previous sections on smaller inputs.

However, when initially running these experiments, we found that the blur schedule used to gather the experimental results in Sections 5.2, 5.3 and 5.4 displayed poor scaling for the terapixel input. The “Blur 1D” column in Table 5.7 reports these numbers. The 1D refers to the fact that the schedule was using a one dimensional distribution. When we moved to a two-dimensional distribution (the “Blur 2D” column) the benchmark exhibited much better and superlinear scaling. This provides concrete evidence of the power of distributed Halide: when a particular schedule displays poor scaling, it is a matter of only a simple schedule modification to achieve much better performance, even at these extremely large scales. (Note that due to the increased size and number of ghost zones, the baseline execution of Blur 2D required 66 Cori nodes for an aggregate memory requirement of 8.2 TB) .

## 5.5. Terapixel Results

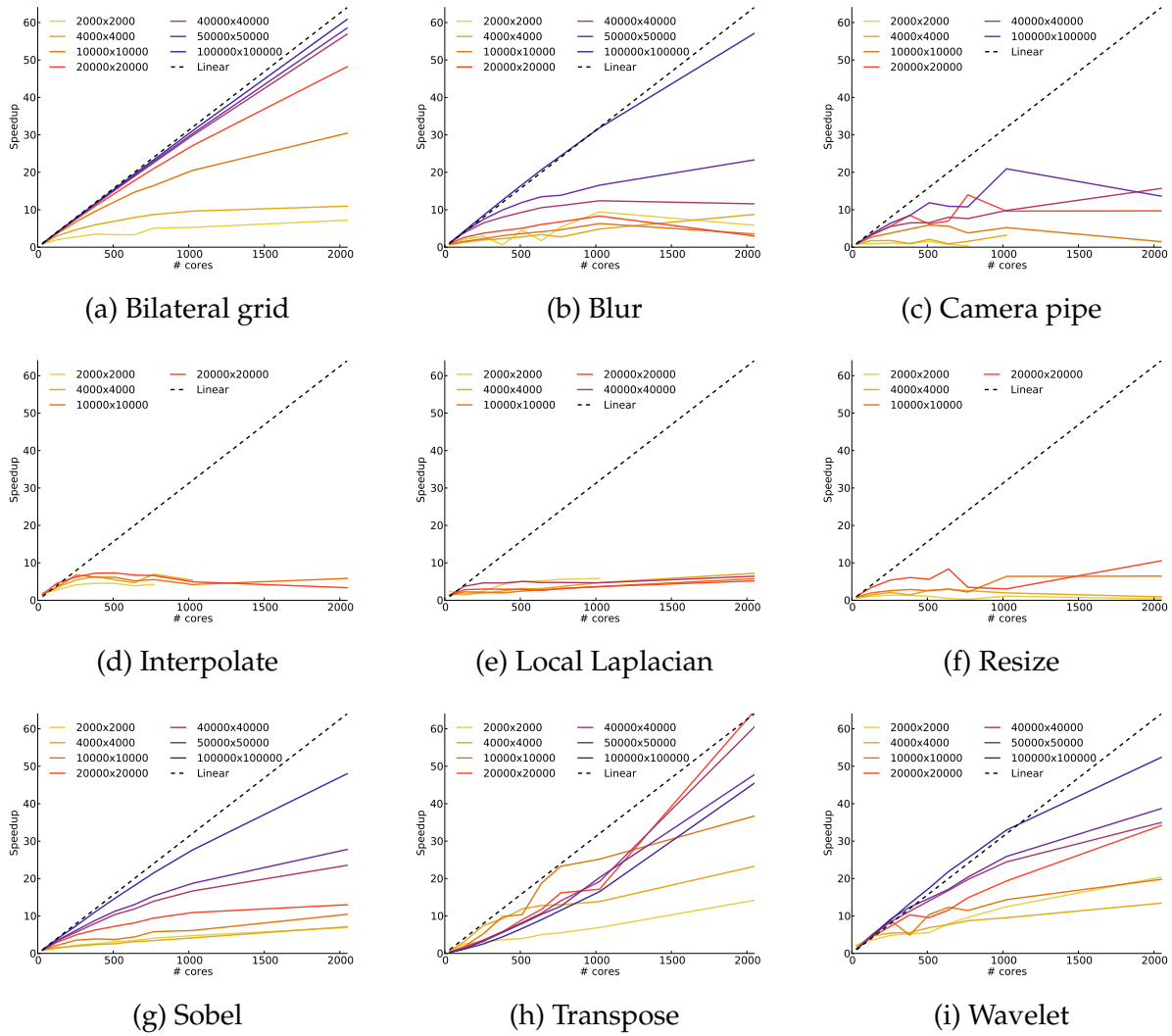


Figure 5.4: Scaling results across all benchmarks with varying input sizes on the Cori supercomputer.

# Chapter 6

## Related Work

**Distributed Scheduling** Finding an optimal allocation of tasks to distributed workers in order to minimize communication is an NP-hard problem in general [15]. As such, there is a wealth of research devoted to approximate algorithms for finding task allocations to minimize communication, e.g. [35, 15, 9, 22, 21, 17]. The distributed Halide compiler does not attempt to automatically determine distributed schedules. This follows the Halide philosophy in allowing the programmer to quickly try many different distributed schedules and empirically arrive at a high-performing distributed schedule. To semi-automate the search process, one can apply an autotuning approach as in [10].

In [16], the authors formulate a static polyhedral analysis algorithm to generate efficient communication code for distributed affine loop nests. This work uses a notion of “flow-out intersection flow-in” sets, derived using polyhedral analy-

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sis, to minimize unnecessary communication present in previous schemes. Our approach of required region intersection is similar to their approach. However, because our code generation can take advantage of domain-specific information available in Halide programs (for example, stencil footprints), our system has additional information that allows our code generation to be much simpler. A more general approach like flow-out intersection flow-in could be used, but would add unnecessary complexity.

**Distributed Languages and Libraries** In [25], an edge-detection benchmark was distributed on a network of workstations. The data partitioning scheme they adopted was to initially distribute all input required by each workstation, meaning no communication was required during execution. However, the software architecture in this work requires the distribution strategy to be implemented on their master workstation, and reimplementing a new data distribution in this architecture requires a non-trivial amount of work.

Some distributed languages such as X10 [12] and Titanium [20] include rich array libraries that allow users to construct distributed multidimensional structured grids, while providing language constructs that make it easy to communicate ghost zones between neighbors. However, exploring schedules for on-node computation requires rewriting large portions of the code.

DataCutter [11] provides a library approach for automatically communicating data requested by range queries on worker processors. Their approach requires



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generating an explicit global indexing structure to satisfy the range queries, where our approach maps data ranges to owners with simple arithmetic.

**Image Processing DSLs** Other than Halide, other efforts at building domain-specific languages for image processing include Forma [32], a DSL by Nvidia for image processing on the GPU and CPU; Darkroom, which compiles image processing pipelines into hardware; and Polymage [27], which implements the subset of Halide for expressing algorithms and uses a model-driven compiler to find a good schedule automatically. None of these implement distributed-memory code generation.

**Stencil DSLs** Physis [26] takes a compiler approach for generating distributed stencil codes on heterogeneous clusters. They implement a high-level language for expressing stencil code algorithms, and their compiler automatically performs optimizations such as overlap of computation and communication. Physis does not have analogy to Halide’s scheduling language, meaning performance of a distributed stencil code completely depends on the automatic compiler optimizations. Other stencil DSLs [33, 23, 14, 19] do not support distributed code generation, though they do generate shared-memory parallel code.

# Chapter 7

## Conclusions and Future Work

In this thesis we proposed several new features for the Halide language to support scheduling pipelines for distributed execution, and evaluated their efficacy. The new language features fit well within the existing Halide language and are simple enough to easily understand, yet powerful enough in composition to express sophisticated data and computation distributions. With the work of this thesis, programmers can quickly experiment to optimize distributed image processing or simulation applications both globally, in terms of communication of shared data, and locally in terms of on-node computation, using a single unified language. Prior to the work presented in this thesis, Halide was restricted to shared-memory execution only, a major limitation for terapixel-and-beyond input sizes.

On nine image processing benchmarks, we demonstrated up to a superlinear

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18 $\times$  speedup on 384 cores distributed across 16 compute nodes and up to 57 $\times$  speedup on 2,048 cores across 64 compute nodes on the NERSC Cori supercomputer. We also demonstrated up to a 1.4 $\times$  speedup on single-node execution by mitigating NUMA architectural effects. We demonstrated near-linear scaling of three benchmarks on terapixel inputs, including a 3D heat stencil, up to 16,384 cores across 512 Cori nodes.

There are a number of intriguing avenues to extend this work in the future. Perhaps the most obvious is to extend distributed Halide to support heterogeneous execution on CPU/GPU distributed systems. As Halide already contains a backend capable of generating GPU code, this is a natural extension. Additionally, many stencil pipelines in both the image processing and simulation domains are very easily adapted to the GPU model of computation, meaning a heterogeneous distributed Halide backend could offer many times better performance on capable systems.

While the scheduling language approach of Halide is orders of magnitude beyond the previous state of the art for optimizing stencil pipeline performance, there is still much to be desired from a user perspective, as finding good schedules can still be a difficult task. Another natural extension of this thesis would be to extend the existing autotuning approach to handle the new distributed Halide constructs. This would allow for automatic search not only for efficient on-node schedules, but also efficient data layouts and computation distributions.

Finally, while autotuning is one potential method for automatic distributed

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scheduling, there is much work in the literature analyzing the performance of distributed stencils, including many models used for performance predictions. These heuristics could be encapsulated in a Halide compiler pass to automatically schedule distributed Halide pipelines. Then, a schedule search either by an autotuner or the programmer can be started from this new baseline, potentially vastly reducing the time to arrive at an optimal schedule.

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# Appendix A

## Distributed Scheduling Tutorial

This appendix contains an overview of the new distributed Halide language features in the context of several examples. Each example builds on the previous one.

### A.1 Halide Introduction

```
#include <Halide.h>

int main(int argc, char **argv) {
    // A non-distributed example to start, a Halide program
    // to brighten a grayscale image. To keep this simple,
    // we'll omit filesystem I/O details and just
    // arithmetically initialize the input image pixel
    // values.
```

```
// Declare and allocate a 100x100 input and output
// image.
Halide::Image<int> input(100, 100), output(100, 100);

// Define the first pipeline stage needed here, which
// simply multiplies input pixels by a brighten factor.
const float factor = 1.25f;
Halide::Func brighten;
Halide::Var x, y;
brighten(x, y) = factor * input(x, y);

// Define a second pipeline stage to convert the new
// pixel values back to integers and clamp their values
// to [0,255].
Halide::Func clampint;
clampint(x, y) = clamp(Halide::cast<int>(brighten(x, y)),
                      0, 255);

// The definition of the Halide pipeline is
// complete. Now we compile it..
clampint.compile_jit();

// ...initialize the input with an arithmetic
// progression...
for (int y = 0; y < input.height(); y++) {
    for (int x = 0; x < input.width(); x++) {
        input(x, y) = x + y;
    }
}
```

```
// ...and execute it into the output image.
clampint.realize(output);

return 0;
}
```

## A.2 Distributing a Pipeline

```
#include <Halide.h>
#include <mpi.h>

int main(int argc, char **argv) {
    // We'll take the pipeline from the previous example and
    // turn it into a distributed pipeline using the new
    // language features.

    // This is now an MPI program, so we need to initialize
    // the MPI library.
    MPI_Init(&argc, &argv);

    // Declare and allocate a 100x100 input and output
    // image. Now that these are DistributedImages, the
    // 100x100 refers to the global extents, not the extents
    // on each rank.
    Halide::DistributedImage<int> input(100, 100),
        output(100, 100);

    // The pipeline definition (i.e. the algorithm) is
    // identical to the non-distributed example. Nothing
    // changes here.
    const float factor = 1.25f;
```

```
Halide::Func brighten;
Halide::Var x, y;
brighten(x, y) = factor * input(x, y);

// Define a second pipeline stage to convert the new
// pixel values back to integers and clamp their values
// to [0,255].
Halide::Func clampint;
clampint(x, y) = clamp(Halide::cast<int>(brighten(x, y)),
                      0, 255);

// Now distribute the pipeline on the y dimension. Each
// rank will be responsible for computing a contiguous
// "slice" of rows for the 'clampint' stage. The
// 'brighten' stage is unscheduled, which means the
// 'brighten' function will be inlined into 'clampint'.
clampint.distribute(y);

// The definition and scheduling of the distributed
// Halide pipeline is complete. Now we can specify the
// data distribution. This has to occur after scheduling
// the pipeline so that the input image can be allocated
// with room for any border exchanges (here there are
// none). Here we specify both the input and output
// images should also be distributed on the y dimension.
input.set_domain(x, y);
input.placement().distribute(y);
input.allocate();

output.set_domain(x, y);
output.placement().distribute(y);
```

```
output.allocate();

// Compile.
clampint.compile_jit();

// Initialize the pixel values with an arithmetic
// progression. Now the x and y iterate over the
// rank-local section of 'input'. We can access the
// global extents with 'input.global_height()' and
// 'input.global_width()'.
for (int y = 0; y < input.height(); y++) {
    for (int x = 0; x < input.width(); x++) {
        // Because x and y are local coordinates, we use
        // the DistributedImage::global() function to
        // convert local x to global x and local y to
        // global y.
        const int global_x = input.global(0, x);
        const int global_y = input.global(1, y);
        input(x, y) = global_x + global_y;
    }
}

// Execute it into the rank-local portion of the output
// image.
clampint.realize(output);

MPI_Finalize();
return 0;
}
```

## A.3 Distributed Pipeline with Communication

```
#include <Halide.h>
#include <mpi.h>

int main(int argc, char **argv) {
    // The previous example, while a proper distributed
    // pipeline, did not actually involve any
    // communication. The pipeline stencils were pointwise,
    // meaning they did not access neighboring pixels, and
    // thus each rank had all of the data it needed to
    // compute everything locally. Now we move to a new
    // example, the 3x3 box blur, which does involve
    // communication.

    // Initialize the MPI library.
    MPI_Init(&argc, &argv);

    // Declare and allocate a 100x100 input and output
    // image.
    Halide::DistributedImage<int> input(100, 100),
        output(100, 100);

    // Because our pipeline now accesses the input image
    // through a stencil, we need to impose a boundary
    // condition which specifies what to do when attempting
    // out-of-bounds accesses. Here we impose a simple
    // clamp-to-edge boundary condition. Note that the x, y
    // coordinates are being clamped to the global extents
    // of the input image. This means that accesses on a
    // particular rank may be to pixels owned by a different
```



### A.3. Distributed Pipeline with Communication

---

```
// rank, but no rank will access pixels outside of the
// global input image.
Halide::Func clamped;
Halide::Var x, y;
clamped(x, y) = input(clamp(x, 0, input.global_width()-1),
                      clamp(y, 0, input.global_height()-1));
// The definition of the 3x3 box blur in two stages. The
// algorithm definition contains no special syntax to
// indicate that there may be communication needed: the
// communication is inferred by the compiler passes.
Halide::Func blur_x, blur_y;
blur_x(x, y) = (clamped(x-1, y) +
               clamped(x, y) +
               clamped(x+1, y))/3;
blur_y(x, y) = (blur_x(x, y-1) +
               blur_x(x, y) +
               blur_x(x, y+1))/3;

// We'll give a simple distributed schedule to the
// pipeline: compute both stages separately, both
// distributed on the y dimension.
blur_x.compute_root().distribute(y);
blur_y.compute_root().distribute(y);

// Allocate the images now that the pipeline is
// scheduled. Note that now we must pass the last stage
// of the pipeline to the allocate() function for
// 'input': this is so that the local portion of 'input'
// can be allocated large enough for any border exchange
// to happen.
input.set_domain(x, y);
```

### A.3. Distributed Pipeline with Communication

---

```
input.placement().distribute(y);
input.allocate(blur_y, output);

output.set_domain(x, y);
output.placement().distribute(y);
output.allocate();

// Compile.
blur_y.compile_jit();

// Initialize the pixel values with an arithmetic
// progression.
for (int y = 0; y < input.height(); y++) {
    for (int x = 0; x < input.width(); x++) {
        const int global_x = input.global(0, x);
        const int global_y = input.global(1, y);
        input(x, y) = global_x + global_y;
    }
}

// Execute it into the rank-local portion of the output
// image. Communication code has been generated for the
// border exchanges. Because we distributed everything
// along the y dimension, there will be no communication
// for 'input' because 'blur_x' does not access input
// through a stencil in the y dimension. However, there
// will be communication of the intermediate 'blur_x'
// buffer in order to compute 'blur_y'. Each rank will
// need to send and receive the top and bottommost rows
// to and from its neighboring ranks.
blur_y.realize(output);
```

```
MPI_Finalize();
return 0;
}
```

## A.4 Using `compute_rank()`

```
#include <Halide.h>
#include <mpi.h>

int main(int argc, char **argv) {
    // This example builds on the box blur, but illustrates
    // the use of the new compute_rank() scheduling
    // directive.

    // Initialize the MPI library.
    MPI_Init(&argc, &argv);

    // Declare and allocate a 100x100 input and output
    // image.
    Halide::DistributedImage<int> input(100, 100),
        output(100, 100);

    // Impose a simple clamp-to-edge boundary condition.
    Halide::Func clamped;
    Halide::Var x, y;
    clamped(x, y) = input(clamp(x, 0, input.global_width()-1),
                          clamp(y, 0, input.global_height()-1));
    // The definition of the 3x3 box blur in two stages.
    Halide::Func blur_x, blur_y;
    blur_x(x, y) = (clamped(x-1, y) +
```

```
        clamped(x, y) +
        clamped(x+1, y))/3;
blur_y(x, y) = (blur_x(x, y-1) +
               blur_x(x, y) +
               blur_x(x, y+1))/3;

// We schedule the first stage using the new
// compute_rank() directive. The second stage is
// scheduled as before.
blur_x.compute_rank();
blur_y.compute_root().distribute(y);

// Allocate the images now that the pipeline is
// scheduled.
input.set_domain(x, y);
input.placement().distribute(y);
input.allocate(blur_y, output);

output.set_domain(x, y);
output.placement().distribute(y);
output.allocate();

// Compile.
blur_y.compile_jit();

// Initialize the pixel values with an arithmetic
// progression.
for (int y = 0; y < input.height(); y++) {
    for (int x = 0; x < input.width(); x++) {
        const int global_x = input.global(0, x);
        const int global_y = input.global(1, y);
```

```

        input(x, y) = global_x + global_y;
    }
}

// Execute it into the rank-local portion of the output
// image. In the previous example, there was no
// communication of the 'input' buffer in order to
// compute 'blur_x'. However, the meaning of
// compute_rank is to compute all of the particular
// function required to compute all of its consumers
// locally. The only consumer of 'blur_x' is
// 'blur_y'. Because 'blur_y' *does* access input
// through a stencil in the y dimension, now 'blur_x'
// needs the additional top and bottom rows of input to
// compute the necessary region. Therefore, in this new
// schedule, there will be communication of 'input' to
// compute 'blur_x', but *no communication* of 'blur_x'
// to compute 'blur_y', which is the definition of
// compute_rank.
blur_y.realize(output);

MPI_Finalize();
return 0;
}

```

## A.5 Nested Distribution

```

#include <Halide.h>
#include <mpi.h>

int main(int argc, char **argv) {

```

```
// This final example also uses the box blur, but
// illustrates the use of nested distribution composing
// with compute_rank().

// Initialize the MPI library.
int rank = 0, numprocs = 0;
MPI_Init(&argc, &argv);
MPI_Comm_rank(MPI_COMM_WORLD, &rank);
MPI_Comm_size(MPI_COMM_WORLD, &numprocs);

// Declare and allocate a 100x100 input and output
// image.
Halide::DistributedImage<int> input(100, 100),
    output(100, 100);

// Impose a simple clamp-to-edge boundary condition.
Halide::Func clamped;
Halide::Var x, y;
clamped(x, y) = input(clamp(x, 0, input.global_width()-1),
    clamp(y, 0, input.global_height()-1));
// The definition of the 3x3 box blur in two stages.
Halide::Func blur_x, blur_y;
blur_x(x, y) = (clamped(x-1, y) +
    clamped(x, y) +
    clamped(x+1, y))/3;
blur_y(x, y) = (blur_x(x, y-1) +
    blur_x(x, y) +
    blur_x(x, y+1))/3;

// We schedule the first stage using the new
// compute_rank() directive. The second stage is now
```

```
// scheduled as nested 2D distribution.
blur_x.compute_rank();

// Use the utility 'approx_factors_near_sqrt' function.
auto proc_grid = Halide::approx_factors_near_sqrt(numprocs);
int p = proc_grid.first, q = proc_grid.second;
if (rank == 0) printf("Using process grid %dx%d\n", p, q);
blur_y.compute_root().distribute(x, y, p, q);

// Allocate the images now that the pipeline is
// scheduled. 2D distribution on the data as well.
input.set_domain(x, y);
input.placement().distribute(x, y, p, q);
input.allocate(blur_y, output);

output.set_domain(x, y);
output.placement().distribute(x, y, p, q);
output.allocate();

// Compile.
blur_y.compile_jit();

// Initialize the pixel values with an arithmetic
// progression.
for (int y = 0; y < input.height(); y++) {
    for (int x = 0; x < input.width(); x++) {
        const int global_x = input.global(0, x);
        const int global_y = input.global(1, y);
        input(x, y) = global_x + global_y;
    }
}
```

```
// Execute it into the rank-local portion of the output
// image. Now each processor computes a 2D section of
// the output image, the exact extents of which depend
// on the number of MPI ranks available at runtime. If
// you compile this and run with different numbers of
// ranks, you will see the processor grid message
// changes to reflect the difference.
blur_y.realize(output);

MPI_Finalize();
return 0;
}
```