Lecture 4:
Efficiently Scheduling Image Processing Pipelines

Visual Computing Systems
Stanford CS348K, Spring 2020
Today’s lecture: two themes

- Techniques for efficiently mapping image processing applications to multi-core CPUs and GPUs

- The design of programming abstractions that facilitate efficient image processing applications
Key aspect in the design of any system:
Choosing the “right” representations for the job
Choosing the “right” representation for the job

- Good representations are productive to use:
  - They embody the natural way of thinking about a problem

- Good representations enable the system to provide the application developer useful services:
  - Validating/providing certain guarantees (correctness, resource bounds, conversation of quantities, type checking)
  - Performance optimizations (parallelization, vectorization, use of specialized hardware)
  - Implementations of common, difficult-to-implement functionality (texture mapping and rasterization in 3D graphics, auto-differentiation in ML frameworks)
void mystery (const Image &in, Image &output) {
  __m128i one_third = __mm_set1_epi16(21846);
  #pragma omp parallel for
  for (int yTile = 0; yTile < in.height(); yTile += 32) {
    __m128i a, b, c, sum, avg;
    __m128i tmp[(256/8)*(32+2)];
    for (int xTile = 0; xTile < in.width(); xTile += 256) {
      __m128i *tmpPtr = tmp;
      for (int y = -1; y < 32+1; y++) {
        const uint16_t *inPtr = &(in(xTile, yTile+y));
        for (int x = 0; x < 256; x += 8) {
          a = __mm_loadu_si128((__m128i*)(inPtr-1));
          b = __mm_loadu_si128((__m128i*)(inPtr+1));
          c = __mm_load_si128((__m128i*)(inPtr));
          sum = __mm_add_epi16(__mm_add_epi16(a, b), c);
          avg = __mm_mulhi_epi16(sum, one_third);
          __mm_store_si128(tmpPtr++, avg);
          inPtr += 8;
        }
        tmpPtr = tmp;
      }
      __m128i *outPtr = (__m128i*)(&output(xTile, yTile+y));
      for (int x = 0; x < 256; x += 8) {
        a = __mm_load_si128(tmpPtr+(2*256)/8);
        b = __mm_load_si128(tmpPtr+256/8);
        c = __mm_load_si128(tmpPtr++);
        sum = __mm_add_epi16(__mm_add_epi16(a, b), c);
        avg = __mm_mulhi_epi16(sum, one_third);
        __mm_store_si128(outPtr++, avg);
      }
    }
  }
}

I’ll tell you later in class.
Consider a single task: sharpen an image

\[ F = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix} \]
Four different representations of sharpen

1. `float input[(WIDTH+2) * (HEIGHT+2)];
   float output[WIDTH * HEIGHT];`

2. `float weights[] = {0., -1., 0.,
   -1., 5, -1.,
   0., -1., 0.};`

   ```cpp
   for (int j=0; j<HEIGHT; j++) {
       for (int i=0; i<WIDTH; i++) {
           float tmp = 0.f;
           for (int jj=0; jj<3; jj++)
               for (int ii=0; ii<3; ii++)
                   tmp += input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*3 + ii];
           output[j*WIDTH + i] = tmp;
       }
   }
   ```

3. `Image input;
   Image output = convolve(input, F);`

4. `Image input;
   Image output = sharpen(input);`

   ```cpp
   float input[(WIDTH+2) * (HEIGHT+2)];
   float output[WIDTH * HEIGHT];

   float weights[] = {0., -1., 0.,
   -1., 5, -1.,
   0., -1., 0.};

   for (int j=0; j<HEIGHT; j++) {
       for (int i=0; i<WIDTH; i++) {
           float tmp = 0.f;
           for (int jj=0; jj<3; jj++)
               for (int ii=0; ii<3; ii++)
                   tmp += input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*3 + ii];
           output[j*WIDTH + i] = tmp;
       }
   }
   ```
Image processing tasks from previous lectures

Sobel Edge Detection

\[ G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \ast I \]

\[ G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \ast I \]

\[ G = \sqrt{G_x^2 + G_y^2} \]

3x3 Gaussian blur

\[ F = \begin{bmatrix} .075 & .124 & .075 \\ .124 & .204 & .124 \\ .075 & .124 & .075 \end{bmatrix} \]

2x2 downsampling (via averaging)

\[ \text{output}[x][y] = \frac{(\text{input}[2x][2y] + \text{input}[2x+1][2y] + \text{input}[2x][2y+1] + \text{input}[2x+1][2y+1])}{4.f}; \]

Gamma Correction

\[ \text{output}[x][y] = \text{pow}(\text{input}[x][y], 0.5f); \]

LUT-based correction

\[ \text{output}[x][y] = \text{lookup_table}[\text{input}[x][y]]; \]

Histogram

\[ \text{bin}[\text{input}[x][y]]++; \]

Local Pixel Clamp

float f(image input) {
    float min_value = min( min(input[x-1][y], input[x+1][y]),
                           min(input[x][y-1], input[x][y+1]) );
    float max_value = max( max(input[x-1][y], input[x+1][y]),
                           max(input[x][y-1], input[x][y+1]) );
    output[x][y] = clamp(min_value, max_value, input[x][y]);
    output[x][y] = f(input);
Let’s consider representations for authoring image processing applications
Image processing workload characteristics

- **Structure:** sequences (more precisely: DAGs) of operations on images
- **Natural to think about algorithms in terms of their local behavior:** e.g., output at pixel \((x,y)\) is function of input pixels in neighborhood around \((x,y)\)
- **Common case:** computing value of output pixel \((x,y)\) depends on access to a bounded local “window” of input image pixels around \((x,y)\)
- **Some algorithms require data-dependent data access** (e.g., data-dependent access to lookup-tables)
- **Upsampling/downsampling** (e.g., to create image pyramids)
- **Computations that reduce information across many pixels** (e.g., building a histogram, computing maximum brightness pixel in an image)
Goals

- Expressive: facilitate intuitive expression of a broad class of image processing applications
  - e.g., all the components of a modern camera RAW pipeline

- High performance: want to generate code that efficiently utilizes the multi-core and SIMD processing resources of modern CPUs and GPUs, and is memory bandwidth efficient
Halide language

Simple domain-specific language embedded in C++ for describing sequences of image processing operations

```
Var x, y;
Func blurx, blury, bright, out;
Halide::Buffer<uint8_t> in = load_image("myimage.jpg");
Halide::Buffer<uint8_t> lookup = load_image("s_curve.jpg");  // 255-pixel 1D image

// perform 3x3 box blur in two-passes
blurx(x,y) = 1/3.f * (in(x-1,y) + in(x,y) + in(x+1,y));
blury(x,y) = 1/3.f * (blurx(x,y-1) + blurx(x,y) + blurx(x,y+1));

// brighten blurred result by 25%, then clamp
bright(x,y) = min(blury(x,y) * 1.25f, 255);

// access lookup table to contrast enhance
out(x,y) = lookup(bright(x,y));

// execute pipeline to materialize values of out in range (0:800,0:600)
Halide::Buffer<uint8_t> result = out.realize(800, 600);
```

- Functions map integer coordinates to values (e.g., colors of corresponding pixels)
- Value of `blurx` at coordinate `(x,y)` is given by expression accessing three values of `in`

Halide function: an infinite (but discrete) set of values defined on N-D domain

Halide expression: a side-effect free expression that describes how to compute a function’s value at a point in its domain in terms of the values of other functions.
Image processing as a DAG

- myimage.jpg
  - input
  - blurx
  - blury
  - brighten
  - output

- s_curve.jpg
  - lookup
More Halide language (multi-stage functions)

Var x;
Func histogram, average;
Halide::buffer<uint8_t> in = load_image(“myimage.jpg”);

// declare “reduction domain” to be size of input image
RDom r(0, in.width(), 0, in.height());

/////////////////////////////////////////////////////////////////////
// compute avg of image pixels
/////////////////////////////////////////////////////////////////////
average(0) = 0;  // initialize average to 0

// “update definitions” on average: for all points in domain r do update
average(0) += in(r.x, r.y);
average(0) /= in.width() * in.height();
Halide::Buffer<uint8_t> avg_result = avg.realize(1);

/////////////////////////////////////////////////////////////////////
// Compute a histogram
/////////////////////////////////////////////////////////////////////

histogram(x) = 0;  // clear all bins of the histogram to 0

// “update definition” on histogram: for all points in domain r, increment
// appropriate histogram bin
histogram(in(r.x, r.y)) += 1;
Halide::Buffer<uint8_t> hist_result = histogram.realize(256);
Key aspects of representation

- Intuitive expression:
  - Adopts local “point wise” view of expressing algorithms
  - Halide language is declarative. It does not define order of iteration over elements in a domain, or even what values in domain are stored!
    - It only defines what operations are needed to compute these values.
    - Iteration over domain points is implicit (no explicit loops)

```cpp
Var x, y;
Func blurx, out;
Halide::Buffer<uint8_t> in = load_image("myimage.jpg");

// perform 3x3 box blur in two-passes
blurx(x,y) = 1/3.f * (in(x-1,y)    + in(x,y)      + in(x+1,y));
out(x,y) =   1/3.f * (blurx(x,y-1) + blurx(x,y) + blurx(x,y+1));

// execute pipeline on domain of size 800x600
Halide::Buffer<uint8_t> result = out.realize(800, 600);
```
Efficiently executing Halide programs
Halide blur example

Consider writing code for a basic 3x3 convolution

Var x, y;
Func blurx, out;
Image< uint8_t > in = load_image("myimage.jpg");

out(x,y) = 1/9.f * (in(x-1,y-1) + in(x,y-1) + in(x+1,y-1) +
                     in(x-1,y)   + in(x,y)   + in(x+1,y) +
                     in(x-1,y+1) + in(x,y+1) + in(x+1,y+1) );

// execute pipeline on domain of size 1024x1024
Image< uint8_t > result = out.realize(1024, 1024);

Total work per output image = 9 x WIDTH x HEIGHT
For NxN filter: N^2 x WIDTH x HEIGHT
Halide blur example

Consider writing code for a two-pass 3x3 image blur

Var x, y;
Func blurx, out;
Image<uint8_t> in = load_image("myimage.jpg");

// perform 3x3 box blur in two-passes (box blur is separable)
blurx(x,y) = 1/3.f * (in(x-1,y) + in(x,y) + in(x+1,y));
out(x,y) = 1/3.f * (blurx(x,y-1) + blurx(x,y) + blurx(x,y+1));

// execute pipeline on domain of size 1024x1024
Image<uint8_t> result = out.realize(1024, 1024);

Total work per output image = 6 x WIDTH x HEIGHT
Two-pass 3x3 blur (naive C implementation)

int WIDTH = 1024;
int HEIGHT = 1024;
float input[(WIDTH+2) * (HEIGHT+2)];
float tmp_buf[WIDTH * (HEIGHT+2)];
float output[WIDTH * HEIGHT];
float weights[] = {1.0/3, 1.0/3, 1.0/3};

for (int j=0; j<(HEIGHT+2); j++)
    for (int i=0; i<WIDTH; i++) {
        float tmp = 0.f;
        for (int ii=0; ii<3; ii++)
            tmp += input[j*(WIDTH+2) + i+ii] * weights[ii];
        tmp_buf[j*WIDTH + i] = tmp;
    }

for (int j=0; j<HEIGHT; j++) {
    for (int i=0; i<WIDTH; i++) {
        float tmp = 0.f;
        for (int jj=0; jj<3; jj++)
            tmp += tmp_buf[(j+jj)*WIDTH + i] * weights[jj];
        output[j*WIDTH + i] = tmp;
    }
}

Total work per image = 6 x WIDTH x HEIGHT
For NxN filter: 2N x WIDTH x HEIGHT
WIDTH x HEIGHT extra storage
Two-pass image blur: locality

```
int WIDTH = 1024;
int HEIGHT = 1024;
float input[(WIDTH+2) * (HEIGHT+2)];
float tmp_buf[WIDTH * (HEIGHT+2)];
float output[WIDTH * HEIGHT];
float weights[] = {1.0/3, 1.0/3, 1.0/3};

for (int j=0; j<(HEIGHT+2); j++)
  for (int i=0; i<WIDTH; i++) {
    float tmp = 0.f;
    for (int ii=0; ii<3; ii++)
      tmp += input[j*(WIDTH+2) + i+ii] * weights[ii];
    tmp_buf[j*WIDTH + i] = tmp;
  }

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    float tmp = 0.f;
    for (int jj=0; jj<3; jj++)
      tmp += tmp_buf[(j+jj)*WIDTH + i] * weights[jj];
    output[j*WIDTH + i] = tmp;
  }
}
```

Intrinsic bandwidth requirements of algorithm:
Application must read each element of input image and
must write each element of output image.

Data from `input` reused three times. (immediately reused in next
two `i`-loop iterations after first load, never loaded again.)
- Perfect cache behavior: never load required data more than once
- Perfect use of cache lines (don’t load unnecessary data into cache)

Data from `tmp_buf` reused three times (but three
rows of image data are accessed in between)
- Never load required data more than once… if
  cache has capacity for three rows of image
- Perfect use of cache lines (don’t load unnecessary
data into cache)
Two-pass image blur, “chunked” (version 1)

```c
int WIDTH = 1024;
int HEIGHT = 1024;
float input[(WIDTH+2) * (HEIGHT+2)];
float tmp_buf[WIDTH * 3];
float output[WIDTH * HEIGHT];

float weights[] = {1.0/3, 1.0/3, 1.0/3};

for (int j=0; j<HEIGHT; j++) {
    for (int j2=0; j2<3; j2++)
        for (int i=0; i<WIDTH; i++) {
            float tmp = 0.f;
            for (int ii=0; ii<3; ii++)
                tmp += input[(j+j2)*(WIDTH+2) + i+ii] * weights[ii];
            tmp_buf[j2*WIDTH + i] = tmp;
        }
    for (int i=0; i<WIDTH; i++) {
        float tmp = 0.f;
        for (int jj=0; jj<3; jj++)
            tmp += tmp_buf[jj*WIDTH + i] * weights[jj];
        output[j*WIDTH + i] = tmp;
    }
}
```

Only 3 rows of intermediate buffer need to be allocated

Produce 3 rows of tmp_buf (only what’s needed for one row of output)

Combine them together to get one row of output

Total work per row of output:
- step 1: 3 x 3 x WIDTH work
- step 2: 3 x WIDTH work
Total work per image = 12 x WIDTH x HEIGHT

Loads from tmp_buffer are cached (assuming tmp_buffer fits in cache)
Two-pass image blur, “chunked” (version 2)

```c
int WIDTH = 1024;
int HEIGHT = 1024;
float input[(WIDTH+2) * (HEIGHT+2)];
float tmp_buf[WIDTH * (CHUNK_SIZE+2)];
float output[WIDTH * HEIGHT];

float weights[] = {1.0/3, 1.0/3, 1.0/3};

for (int j=0; j<HEIGHT; j+CHUNK_SIZE) {
    for (int j2=0; j2<CHUNK_SIZE+2; j2++)
        for (int i=0; i<WIDTH; i++) {
            float tmp = 0.f;
            for (int ii=0; ii<3; ii++)
                tmp += input[(j+j2)*(WIDTH+2) + i+ii] * weights[ii];
            tmp_buf[j2*WIDTH + i] = tmp;
        }
    for (int j2=0; j2<CHUNK_SIZE; j2++)
        for (int i=0; i<WIDTH; i++) {
            float tmp = 0.f;
            for (int jj=0; jj<3; jj++)
                tmp += tmp_buf[(j2+jj)*WIDTH + i] * weights[jj];
            output[(j+j2)*WIDTH + i] = tmp;
        }
}
```

Sized so entire buffer fits in cache (capture all producer-consumer locality)

Produce enough rows of tmp_buf to produce a CHUNK_SIZE number of rows of output

Produce CHUNK_SIZE rows of output

Total work per chuck of output:
(assume CHUNK_SIZE = 16)
- Step 1: 18 x 3 x WIDTH work
- Step 2: 16 x 3 x WIDTH work
Total work per image: $(34/16) \times 3 \times WIDTH \times HEIGHT = 6.4 \times WIDTH \times HEIGHT$

Trends to idea 6 x WIDTH x HEIGHT as CHUNK_SIZE is increased!
Still not done

- We have not parallelized loops for multi-core execution
- We have not used SIMD instructions to execute loops bodies
- Other basic optimizations: loop unrolling, etc...
Optimized x86 (SSE) implementation of 3x3 box blur

Good: ~10x faster on a quad-core CPU than my original two-pass code
Bad: specific to SSE (not AVX2), CPU-code only, hard to tell what is going on at all!

```c
void fast_blur(const Image &in, Image &blurred) {
    __m128i one_third = _mm_set1_epi16(21846);
    #pragma omp parallel for
    for (int yTile = 0; yTile < in.height(); yTile += 32) {
        __m128i tmp[(256/8)*(32+2)];
        for (int xTile = 0; xTile < in.width(); xTile += 256) {
            __m128i *tmpPtr = tmp;
            for (int y = -1; y < 32+1; y++) {
                const uint16_t *inPtr = &in(xTile, yTile+y);
                for (int x = 0; x < 256; x += 8) {
                    a = _mm_loadu_si128((__m128i*) (inPtr-1));
                    b = _mm_loadu_si128((__m128i*) (inPtr+1));
                    c = _mm_load_si128(__m128i*) (inPtr));
                    sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
                    avg = _mm_mulhi_epi16(sum, one_third);
                    _mm_store_si128(tmpPtr++, avg);
                }
            }
            tmpPtr = tmp;
            for (int y = 0; y < 32; y++) {
                __m128i *outPtr = (__m128i*) (blurred(xTile, yTile+y));
                for (int x = 0; x < 256; x += 8) {
                    a = _mm_load_si128(tmpPtr+((2*256)/8));
                    b = _mm_load_si128(tmpPtr+256/8);
                    c = _mm_load_si128(tmpPtr++);
                    sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
                    avg = _mm_mulhi_epi16(sum, one_third);
                    _mm_store_si128(outPtr++, avg);
                }
            }
        }
    }
}
```
Image processing pipelines feature complex sequences of functions

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Number of Halide functions</th>
</tr>
</thead>
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<td>Two-pass blur</td>
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<tr>
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<td>7</td>
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<tr>
<td>VGG-16 deep network eval</td>
<td>64</td>
</tr>
</tbody>
</table>

Real-world production applications may features hundreds to thousands of functions! Google HDR+ pipeline: over 2000 Halide functions.
Key aspect in the design of any system:
Choosing the “right” representations for the job

Now the job is not expressing an image processing computation, but generating an efficient implementation of a specific Halide program.
A second set of representations for “scheduling”

```cpp
Func blurx, out;
Var x, y, xi, yi;
Halide::Buffer<uint8_t> in = load_image("myimage.jpg");

// the “algorithm description” (declaration of what to do)
blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y)) / 3.0f;
out(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1)) / 3.0f;

// “the schedule” (how to do it)
out.tile(x, y, xi, yi, 256, 32).vectorize(xi, 8).parallel(y);
blurx.compute_at(x).vectorize(x, 8);

// execute pipeline on domain of size 1024x1024
Halide::Buffer<uint8_t> result = out.realize(1024, 1024);
```

Scheduling primitives allow the programmer to specify a high-level “sketch” of how to schedule the algorithm onto a parallel machine, but leave the details of emitting the low-level platform-specific code to the Halide compiler.
Primitives for iterating over domains

Specify both order and how to parallelize (multi-thread, vectorize via SIMD instr)

2D blocked iteration order
Specifying loop iteration order and parallelism

\[
\text{blurx}(x, y) = \frac{(\text{in}(x-1, y) + \text{in}(x, y) + \text{in}(x+1, y))}{3.0f};
\]
\[
\text{out}(x, y) = \frac{(\text{blurx}(x, y-1) + \text{blurx}(x, y) + \text{blurx}(x, y+1))}{3.0f};
\]

Given this schedule for the function “out”...

\[
\text{out.tile}(x, y, xi, yi, 256, 32).\text{vectorize}(xi, 8).\text{parallel}(y);
\]

Halide compiler will generate this parallel, vectorized loop nest for computing elements of \text{out}...

for \(y=0\) to \(\text{num\_tiles\_y}\):
  \(\text{// parallelize this loop over multiple threads}\)
  for \(x=0\) to \(\text{num\_tiles\_x}\):
    for \(yi=0\) to \(32\):
      \(\text{// vectorize body of this loop with SIMD instructions}\)
      for \(xi=0\) to \(256\) by \(8\):
        idx\_x = \(x\times256+xi\);
        idx\_y = \(y\times32+yi\)
        out(idx\_x, idx\_y) = ...
Primitives for how to interleave producer/consumer processing

\[
\text{blurx}(x,y) = \frac{\text{in}(x-1, y) + \text{in}(x,y) + \text{in}(x+1,y)}{3.0f};
\]

\[
\text{out}(x,y) = \frac{\text{blurx}(x,y-1) + \text{blurx}(x,y) + \text{blurx}(x,y+1)}{3.0f};
\]

\text{out}.tile(x, y, xi, yi, 256, 32);

\text{blurx}.compute_root();

-- Do not compute blurx within out's loop nest.
Compute all of blurx, then all of out

allocate buffer for all of \text{blur}(x,y)
for y=0 to HEIGHT:
  for x=0 to WIDTH:
    \text{blurx}(x,y) = ...

for y=0 to num\_tiles\_y:
  for x=0 to num\_tiles\_x:
    for yi=0 to 32:
      for xi=0 to 256:
        idx\_x = x*256+xi;
        idx\_y = y*32+yi
        \text{out}(idx\_x, idx\_y) = ...

-- values of blurx consumed here

all of blurx is computed here
Primitives for how to interleave producer/consumer processing

```
blurx(x,y) = (in(x-1, y) + in(x,y) + in(x+1,y)) / 3.0f;
out(x,y) = (blurx(x,y-1) + blurx(x,y) + blurx(x,y+1)) / 3.0f;

out.tile(x, y, xi, yi, 256, 32);
```

```
blurx.compute_at(out, xi);
```

```
for y=0 to num_tiles_y:
    for x=0 to num_tiles_x:
        for yi=0 to 32:
            for xi=0 to 256:
                idx_x = x*256+xi;
                idx_y = y*32+yi

allocate 3-element buffer for tmp_blurx

// compute 3 elements of blurx needed for out(idx_x, idx_y) here
for (blur_x=0 to 3)
    tmp_blurx(blur_x) = ...

out(idx_x, idx_y) = ...
```

Note: Halide compiler performs analysis that the output of each iteration of the xi loop required 3 elements of blurx
Primitives for how to interleave producer/consumer processing

\[
\text{blurx}(x, y) = \frac{(\text{in}(x-1, y) + \text{in}(x,y) + \text{in}(x+1,y))}{3.0f};
\]
\[
\text{out}(x,y) = \frac{\text{blurx}(x,y-1) + \text{blurx}(x,y) + \text{blurx}(x,y+1))}{3.0f};
\]
\[
\text{out} \text{.tile}(x, y, xi, yi, 256, 32);
\]

\[
\text{blurx} \text{.compute_at}(\text{out}, x);
\]

for \( y=0 \) to num_tiles_y:
  for \( x=0 \) to num_tiles_x:
    allocate 258x34 buffer for tile blurx
    for yi=0 to 32+2:
      for xi=0 to 256+2:
        \( \text{tmp\_blurx}(xi,yi) = // \text{compute blurx from in} \)

    for yi=0 to 32:
      for xi=0 to 256:
        idx_x = x*256+xi;
        idx_y = y*32+yi
        out(idx_x, idx_y) = …
An interesting Halide schedule

\[
\text{blurx}(x, y) = \frac{(\text{in}(x-1, y) + \text{in}(x, y) + \text{in}(x+1, y))}{3.0f};
\]

\[
\text{out}(x, y) = \frac{(\text{blurx}(x, y-1) + \text{blurx}(x, y) + \text{blurx}(x, y+1))}{3.0f};
\]

\[
\text{out}.\text{tile}(x, y, xi, yi, 256, 32);
\]

\[
\text{blurx}.\text{store}_\text{at}(\text{out}, x)
\]
\[
\text{blurx}.\text{compute}_\text{at}(\text{out}, xi);
\]

for \(y=0\) to num\_tiles\_y:
   for \(x=0\) to num\_tiles\_x:

   allocate 258x34 buffer for tile tmp\_blurx

   for \(yi=0\) to 32:
      for \(xi=0\) to 256:
         \(\text{idx}_x = x*256+xi;\)
         \(\text{idx}_y = y*32+yi;\)

         // compute 3 elements of blurx needed for out(\text{idx}_x, \text{idx}_y) here
         for (blur\_x=0 to 3)
            tmp\_blurx(blur\_x) = ...

         out(\text{idx}_x, \text{idx}_y) = ...

Can compiler be smarter?
“Sliding optimization” (reduces redundant computation)

\[
\text{blurx}(x, y) = \frac{(\text{in}(x-1, y) + \text{in}(x, y) + \text{in}(x+1, y))}{3.0f};
\]
\[
\text{out}(x, y) = \frac{(\text{blurx}(x, y-1) + \text{blurx}(x, y) + \text{blurx}(x, y+1))}{3.0f};
\]

\[
\text{out}.\text{tile}(x, y, x_i, y_i, 256, 32);
\]

\[
\text{blurx}.\text{store}_\text{at}(\text{out}, x)
\]
\[
\text{blurx}.\text{compute}_\text{at}(\text{out}, x_i);
\]

for \(y=0\) to num\_tiles\_y:
  for \(x=0\) to num\_tiles\_x:
    allocate 258x34 buffer for tile tmp\_blurx

  for \(y_i=0\) to 32:
    for \(x_i=0\) to 256:
      idx\_x = x*256+x_i;
      idx\_y = y*32+y_i;

      if (yi=0) {
        // compute 3 elements of blurx needed for out(idx\_x, idx\_y) here
        for (blur\_x=0 to 3)
          tmp\_blurx(blur\_x) = ...
      } else
        // only compute one additional element of tmp\_blurx

      out(idx\_x, idx\_y) = ...

Compute necessary elements of blurx within out’s xi loop nest, but fill in tile-sized buffer allocated at x loop nest.

Steady state: only one new element of tmp\_blurx needs to be computed per output
“Folding optimization” (reduces intermediate storage)

\[
\text{blurx}(x,y) = \frac{(\text{in}(x-1, y) + \text{in}(x,y) + \text{in}(x+1,y))}{3.0f};
\]
\[
\text{out}(x,y) = \frac{(\text{blurx}(x,y-1) + \text{blurx}(x,y) + \text{blurx}(x,y+1))}{3.0f};
\]
\[
\text{out}.\text{tile}(x, y, xi, yi, 256, 32);
\]

\[
\text{blurx}.\text{store}_\text{at}(\text{out}, x)
\]
\[
\text{blurx}.\text{compute}_\text{at}(\text{out}, xi);
\]

\[
\text{for } y=0 \text{ to num}_\text{tiles}_y:
\]
\[
\text{for } x=0 \text{ to num}_\text{tiles}_x:
\]
\[
\begin{align*}
\text{allocate 3x256 buffer for tmp_blurx} \\
\text{for } yi=0 \text{ to 32:} \\
\text{for } xi=0 \text{ to 256:}
\end{align*}
\]
\[
\text{idx}_x = x*256+xi; 
\text{idx}_y = y*32+yi;
\]

\[
\begin{align*}
\text{if (yi=0) } \\
// \text{compute 3 elements of blurx needed for out(idx}_x, idx}_y \text{here} \\
\text{for (blur}_x=0 \text{ to 3)} \\
\text{tmp_blurx(blur}_x) = ...
\end{align*}
\]
\[
\text{else}
\]
\[
// \text{only compute one additional element of tmp_blurx}
\]
\[
\text{out}(idx}_x, idx}_y = ...
\]

Compute necessary elements of blurx within out’s xi loop nest, but fill in tile-sized buffer allocated at x loop nest.

Circular buffer of 3 rows

Steady state: only one new element of tmp_blurx needs to be computed per output

Accesses to tmp_blurx modified to access appropriate row of circular buffer: e.g., \((\text{idx}_y+1)%3\)
Summary of scheduling the 3x3 box blur

// the “algorithm description” (declaration of what to do)
blurx(x,y) = (in(x-1, y) + in(x,y) + in(x+1,y)) / 3.0f;
out(x,y)   = (blurx(x,y-1) + blurx(x,y) + blurx(x,y+1)) / 3.0f;

// “the schedule” (how to do it)
out.tile(x, y, xi, yi, 256, 32).vectorize(xi,8).parallel(y);
blurx.compute_at(out, x).vectorize(x, 8);

Equivalent parallel loop nest:

for y=0 to num_tiles_y:  // iters of this loop are parallelized using threads
    for x=0 to num_tiles_x:
        allocate 258x34 buffer for tile blurx
        for yi=0 to 32+2:
            for xi=0 to 256+2 BY 8:
                tmp_blurx(xi,yi) = … // compute blurx from in using 8-wide
                                // SIMD instructions here
                                // compiler generates boundary conditions
                                // since 256+2 isn’t evenly divided by 8
        for yi=0 to 32:
            for xi=0 to 256 BY 8:
                idx_x = x*256+xi;
                idx_y = y*32+yi
                out(idx_x, idx_y) = … // compute out from blurx using 8-wide
                                // SIMD instructions here
What is the philosophy of Halide

- **Programmer** is responsible for describing an image processing algorithm
- **Programmer** has knowledge to schedule application efficiently on machine (but it’s slow and tedious), so give programmer a language to express high-level scheduling decisions
  - Loop structure of code
  - Unrolling / vectorization / multi-core parallelization

- **The system** (Halide compiler) is not smart, it provides the service of mechanically carrying out the nitty gritty details of implementing the schedule using mechanisms available on the target machine (pthreads, AVX intrinsics, CUDA code, etc.)
  - There are deviations from this philosophy in Halide? What are they?
Constraints on language
(to enable compiler to provide desired services)

- Application domain scope: computation on regular N-D domains
- Only feed-forward pipelines (includes special support for reductions and fixed recursion depth)
- All dependencies inferable by compiler
Initial academic Halide results

- Camera RAW processing pipeline
  (Convert RAW sensor data to RGB image)
  - Original: 463 lines of hand-tuned ARM NEON assembly
  - Halide: 2.75x less code, 5% faster

- Bilateral filter
  (Common image filtering operation used in many applications)
  - Original 122 lines of C++
  - Halide: 34 lines algorithm + 6 lines schedule
    - CPU implementation: 5.9x faster
    - GPU implementation: 2x faster than hand-written CUDA
Halide used in practice

- Halide used to implement camera processing pipelines on Google phones
  - HDR+, aspects of portrait mode, etc…
- Industry usage at Instagram, Adobe, etc.
Stepping back: what is Halide?

- Halide is a DSL for helping expert developers optimize image processing code more rapidly
  - Halide does not decide how to optimize a program for a novice programmer
  - Halide provides a small number of primitives for a programmer (that has strong knowledge of code optimization) to rapidly express what optimizations the system should apply
    - parallel, vector, unroll, split, reorder, store_at, compute_at, etc...
  - Halide compiler carries out the mapping of that strategy to a machine
Automatically generating Halide schedules

- **Problem:** it turned out that very few programmers have the ability to write good Halide schedules
  - 80+ programmers at Google write Halide
  - Very small number trusted to write schedules

- **Recent work:** compiler analyzes the Halide program to automatically generate efficient schedules for the programmer [optional reading: Mullapudi 2016, Adams 2019]
  - As of Adams 2019, you’d have to work pretty hard to manually author a schedule that is better than the schedule generated by the Halide autoscheduler
Tonight’s Halide readings

- What is the key intellectual idea of the Halide system?
  - Hint: it is not the declarative language syntax

- What services does Halide provide its users?

- What aspects of the design of Halide allow it to provide those services?

- Keep in mind: the key aspect in the design of any system usually is choosing the “right” representations for the job