Lecture 15:

Scheduling Image Processing Pipelines

Visual Computing Systems
CMU 15-869, Fall 2013

Simple image processing kernel

```
int WIDTH = 1024;
int HEIGHT = 1024;
float input[WIDTH * HEIGHT];
float output[WIDTH * HEIGHT];

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    output[j*WIDTH + i] = 0.5f * input[j*WIDTH + i];
  }
}
```

Point-wise operation: one in, one out

2D convolution with 3x3 filter

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

float weights[] = {1./9, 1./9, 1./9,
                   1./9, 1./9, 1./9,
                   1./9, 1./9, 1./9};

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;
  }
}
```

3x3 box blur (Photoshop)

2X zoom view

Convolution with 3x3 filter

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

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

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;
  }
}
```

Data-dependent filter

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

for (int j=0; j<HEIGHT; j++) {
  for (int i=0; i<WIDTH; i++) {
    float min_value = min( min(input[(j-1)*WIDTH + i], input[(j+1)*WIDTH + i]),
                           min(input[j*WIDTH + i-1], input[j*WIDTH + i+1]) );
    float max_value = max( max(input[(j-1)*WIDTH + i], input[(j+1)*WIDTH + i]),
                           max(input[j*WIDTH + i-1], input[j*WIDTH + i+1]) );
    output[j*WIDTH + i] = clamp(min_value, max_value, input[j*WIDTH + i]);
  }
}
```

Image blur (convolution with 2D filter)

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

float weights[] = {1./9, 1./9, 1./9,
                   1./9, 1./9, 1./9,
                   1./9, 1./9, 1./9};

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;
  }
}
```

Total work = 9 x WIDTH x HEIGHT

For NxN filter: N^2 x WIDTH x HEIGHT

Two-pass image blur

```
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./3, 1./3, 1./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+11] * 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 = 6 x WIDTH x HEIGHT

For NxN filter: 2N x WIDTH x HEIGHT

Separable filter

- **Separable 2D filter is outer product of two 1D filters**
- **Implication:**
  - **Can implement 2D convolution as two 1D convolutions**

$$F = \begin{bmatrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix} \begin{bmatrix} 1/3 & 1/3 & 1/3 \end{bmatrix}$$

$$F = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -1 \end{bmatrix}$$

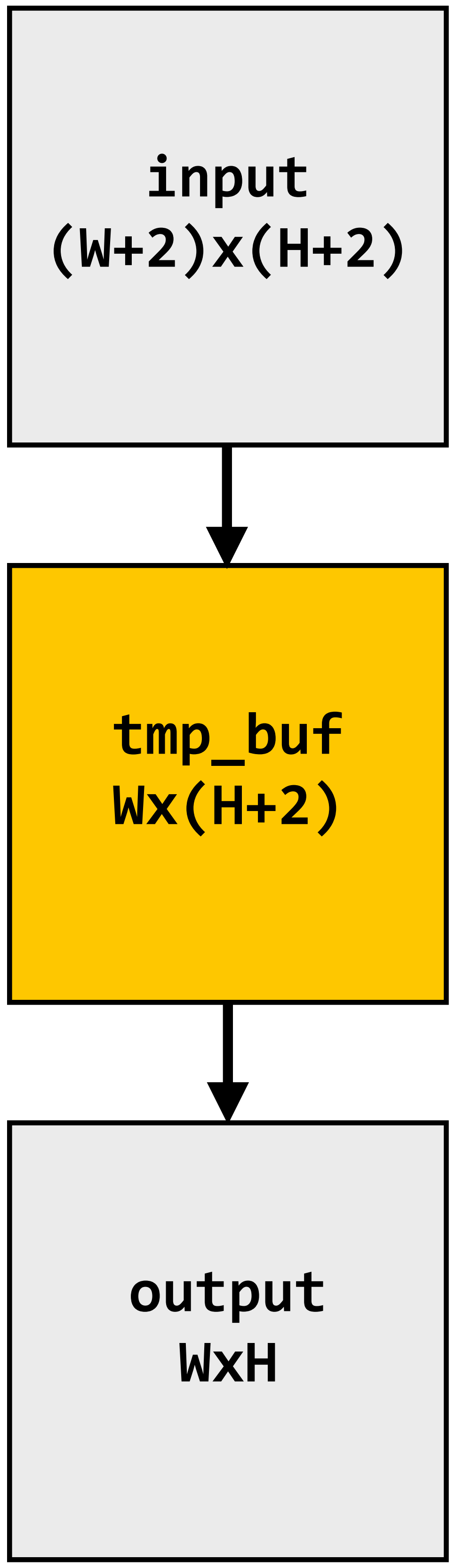
Two-pass image blur

```
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./3, 1./3, 1./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+11] * 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 = 6 x WIDTH x HEIGHT

For NxN filter: 2N x WIDTH x HEIGHT

But ... incurs bandwidth cost of writing and reading tmp_buf. (and footprint overhead of storing tmp_buf)



Two-pass image blur

```
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./3, 1./3, 1./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:
Must read each element of input and must write each element of output.

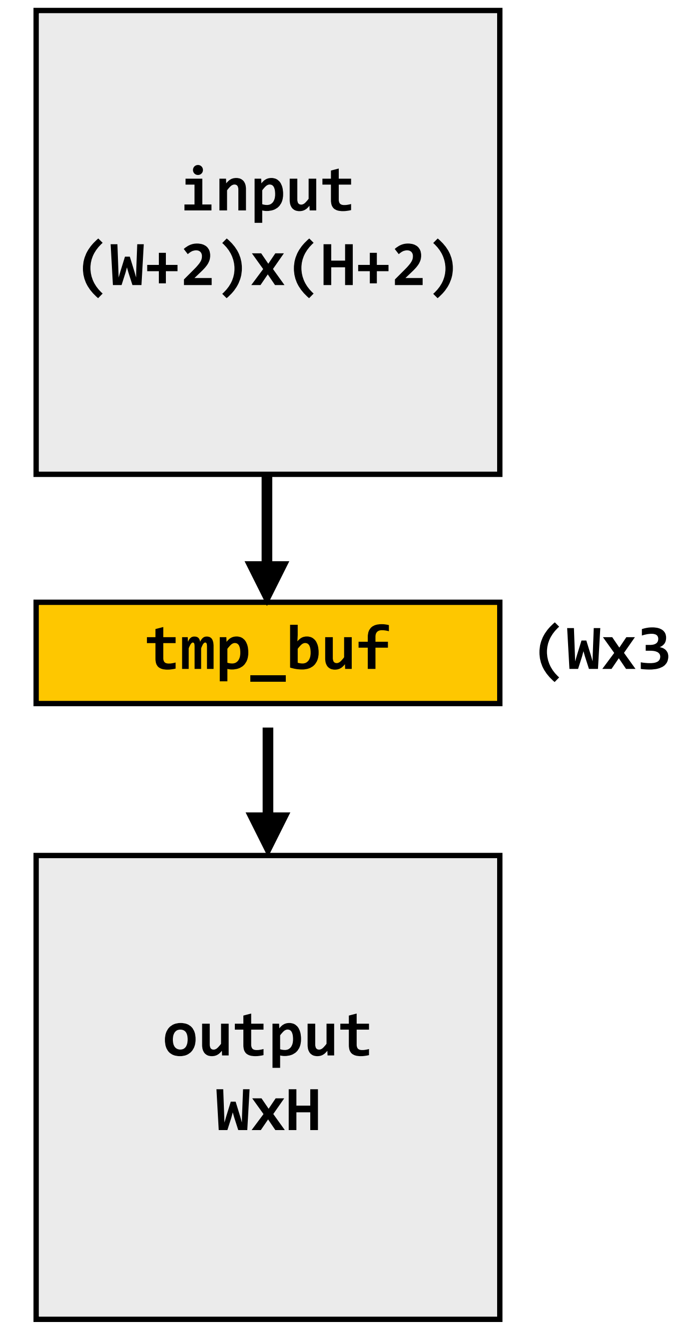
Data from `input` reused 3 times. (immediately reused after first load, never loaded again.) Perfect cache behavior!
- Never load required data more than once
- Perfect use of cache lines (don't load unnecessary data)

Two pass: loads/stores to tmp_buf are overhead (artifact of 2-pass implementation: not intrinsic)

Data from `tmp_buf` reused 3 times (but 3 rows of image data are accessed in between)
- Never load required data more than once if cache can contain <u>three rows of image</u>
- Perfect use of cache lines (don't load unnecessary data)

Two-pass image blur, chunked

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

float weights[] = {1./3, 1./3, 1./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;
  }
}
```



Produce 3 rows of tmp_buf

Combine them together to get one row of output

Total work per row of output:

step 1: 3 rows = 3 x 3W work

step 2: 1 row = 3W work

total: 12 x W x H work ?????

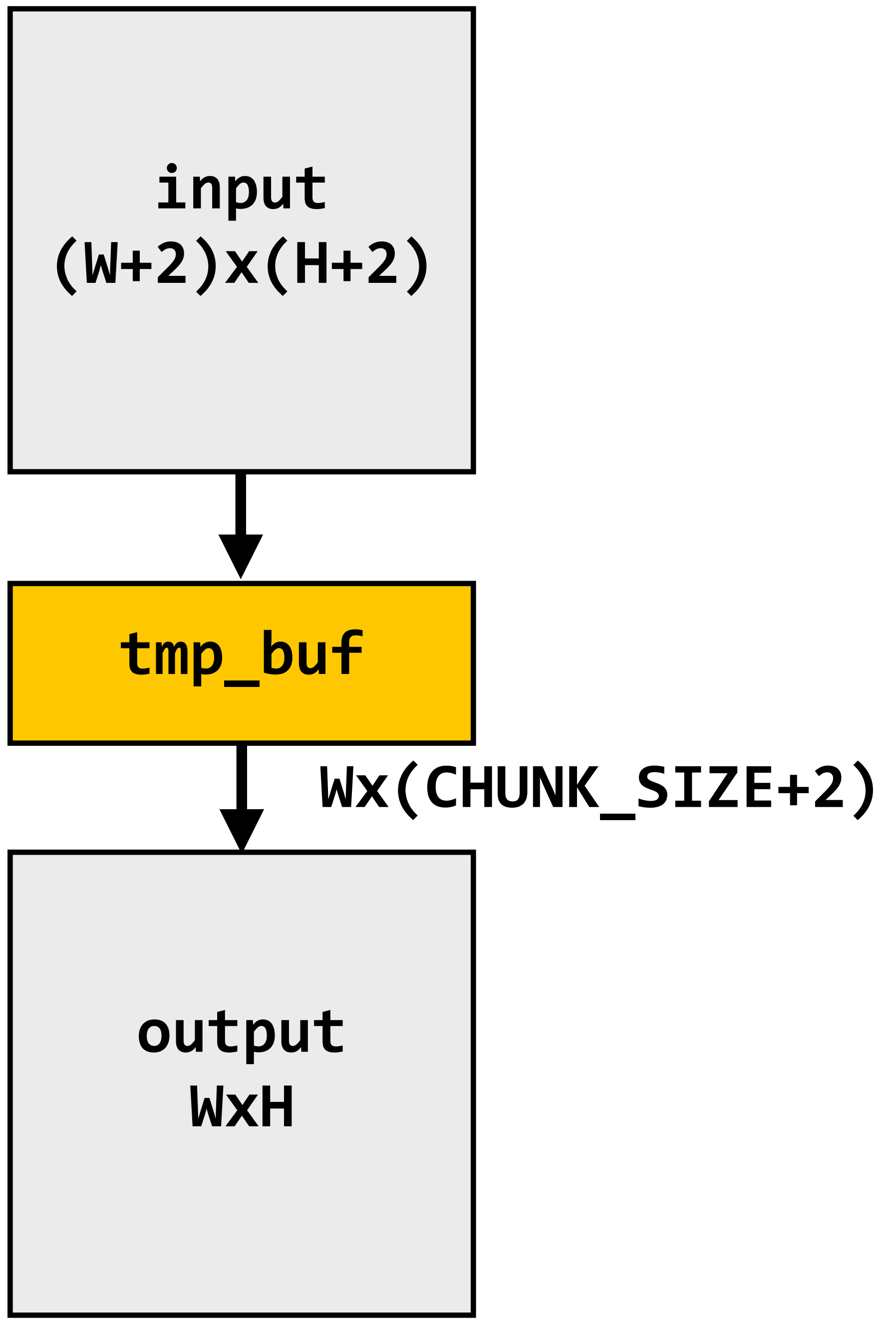
Two-pass image blur, chunked

```
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./3, 1./3, 1./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+11] * 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 to fit 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 row of output:

Let CHUNK_SIZE = 16

step 1: 18 x 3W work

step 2: 16 x 3W work

total: (2 + 2/16) x 3 x W x H work

Conflicting goals (again...)

- Want to be work efficient
- Want to be parallel (multi-core, SIMD within core)
- Want to take advantage of locality when present
  - Ideal: bandwidth cost of implementation is intrinsic cost of algorithm: data loaded from memory once and used in all instances it is needed prior to being discarded from processor's cache

Optimized C++ code: 3x3 image 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!

```
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 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;
   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);
}}}}}
```

Multi-core execution (partition image vertically)

Modified iteration order: 256x32 block-major iteration (to maximize cache hit rate)

use of SIMD vector intrinsics

two passes fused into one: `tmp` data read from cache

Example: Halide Language

Halide blur

- **Halide = two domain-specific co-languages**
  1. A purely functional language for defining image processing algorithms
  2. A mini-language for defining "schedules" for how to map these algorithms to machines

Images are pure functions from integer coordinates (up to 4D domain) to values (color of corresponding pixels)

Algorithms are a series of functions (think: a function is a pipeline stage)

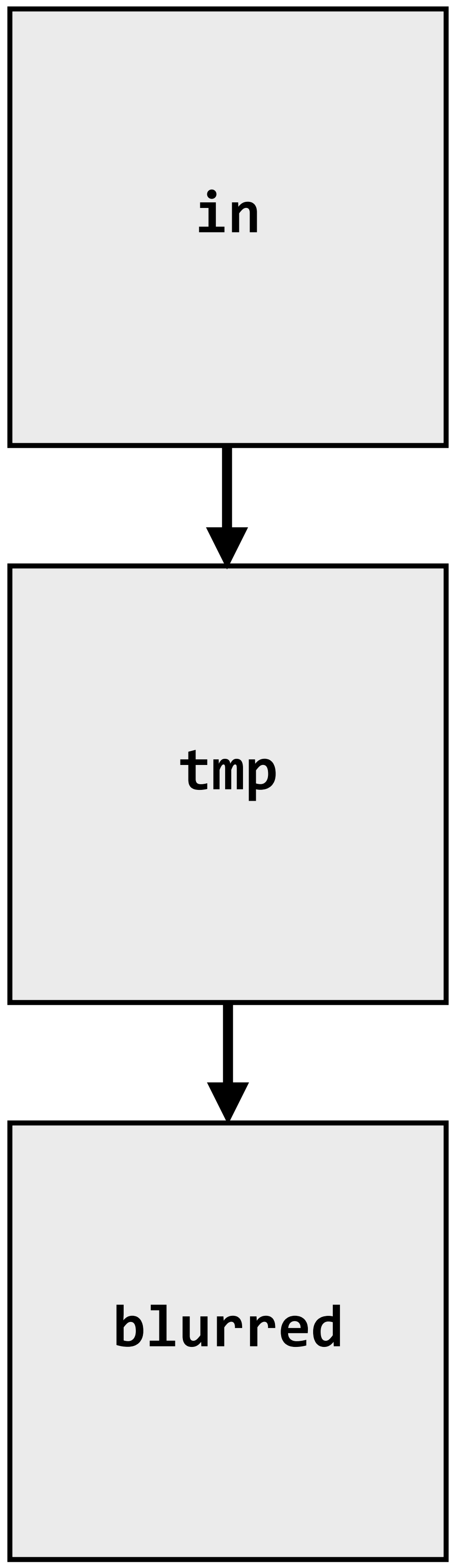
Functions (side-effect-free) map coordinates to values (`in`, `tmp` and `blurred` are functions)

```
Func halide_blur(Func in) {
 Func tmp, blurred;
 Var x, y, xi, yi;

 // The algorithm
 tmp(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
 blurred(x, y) = (tmp(x, y-1) + tmp(x, y) + tmp(x, y+1))/3;

 return blurred;
}
```

NOTE: execution order and storage are unspecified by functional abstraction! Implementation can evaluate, reevaluate, cache individual points as desired!

Halide program as a pipeline

```
Func halide_blur(Func in) {
 Func tmp, blurred;
 Var x, y, xi, yi;

 // The algorithm
 tmp(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
 blurred(x, y) = (tmp(x, y-1) + tmp(x, y) + tmp(x, y+1))/3;




 return blurred;
}
```



Halide blur

- **Halide = two domain-specific co-languages**
  1. A purely functional language for defining image processing algorithms
  2. A mini-language for defining "schedules" for how to map these algorithms to machines

```
Func halide_blur(Func in) {
  Func tmp, blurred;
  Var x, y, xi, yi;

  // The algorithm
  tmp(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
  blurred(x, y) = (tmp(x, y-1) + tmp(x, y) + tmp(x, y+1))/3;

  // The schedule
  blurred.tile(x, y, xi, yi, 256, 32)
         .vectorize(xi, 8).parallel(y);
  tmp.chunk(x).vectorize(x, 8);

  return blurred;
}
```

When evaluating `blurred`, use 2D tiling order (loops named by x, y, xi, yi). Use tile size 256 x 32.

Vectorize the xi loop (8-wide), use threads to parallelize the y loop

Produce only chunks of `tmp` at a time. Vectorize the x (innermost) loop

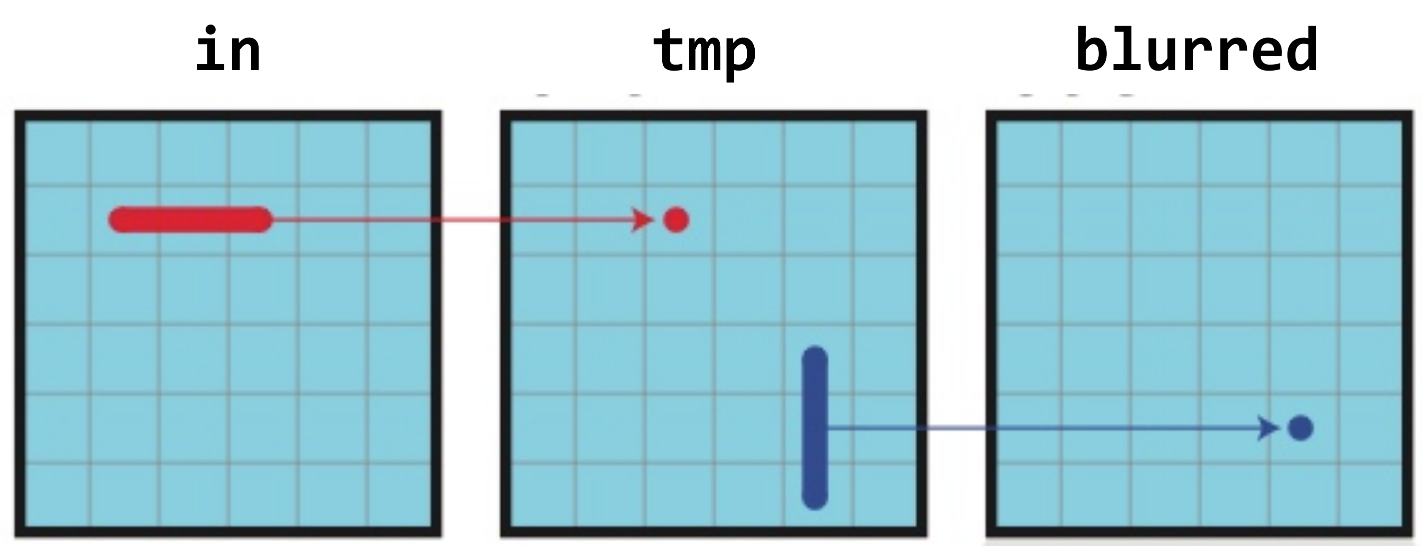
Separation of algorithm from schedule

- **Key idea: separate specification of image processing algorithm (machine independent) from specification of schedule (machine dependent mapping)**

- **Given algorithm and schedule description, Halide attempts to generate high quality code for a target machine**
  - Domain scope:
    - All computation over regular (up to 4D) grids
    - Only feed-forward pipelines (includes special support for reductions)
    - Language constrained so that all dependencies can be inferred by compiler

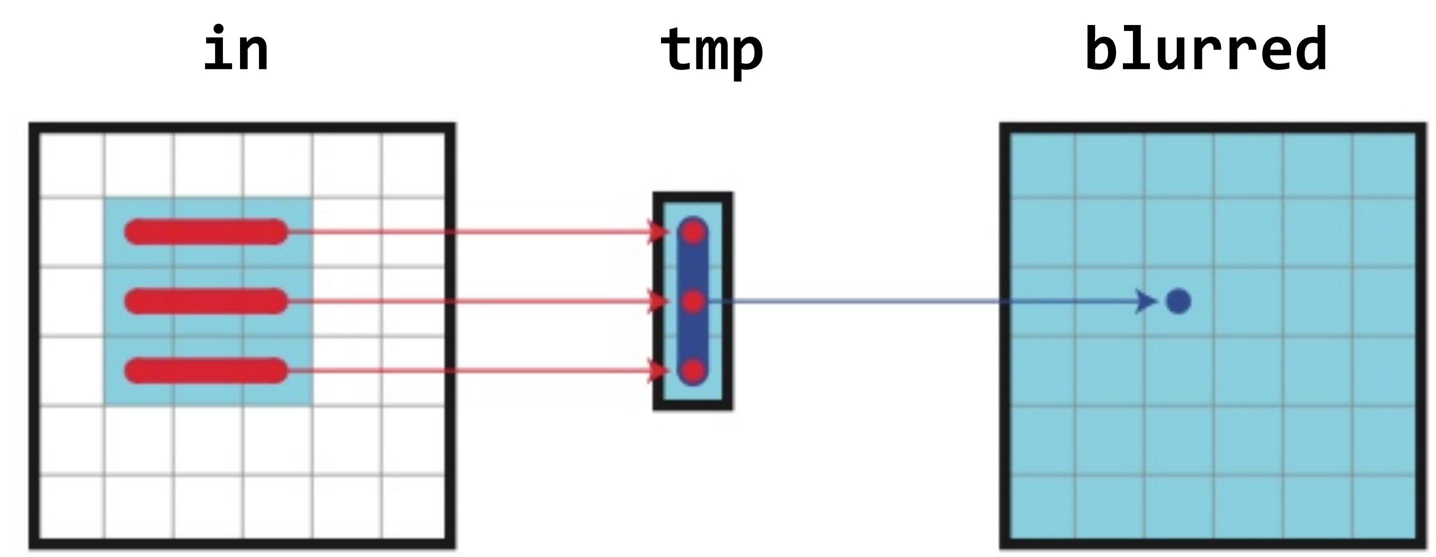
Halide schedule: producer/consumer scheduling

- Four basic scheduling primitives shown below
- Fifth primitive: "reuse" not shown



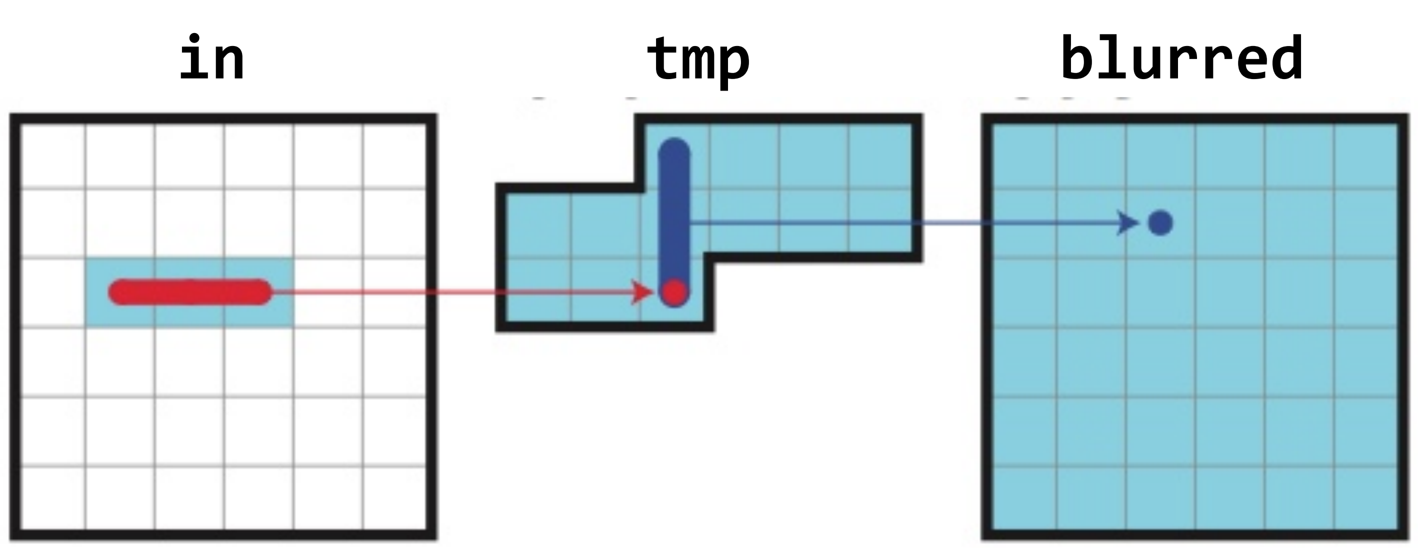
breadth first: each function is entirely evaluated before the next one.

"Root"



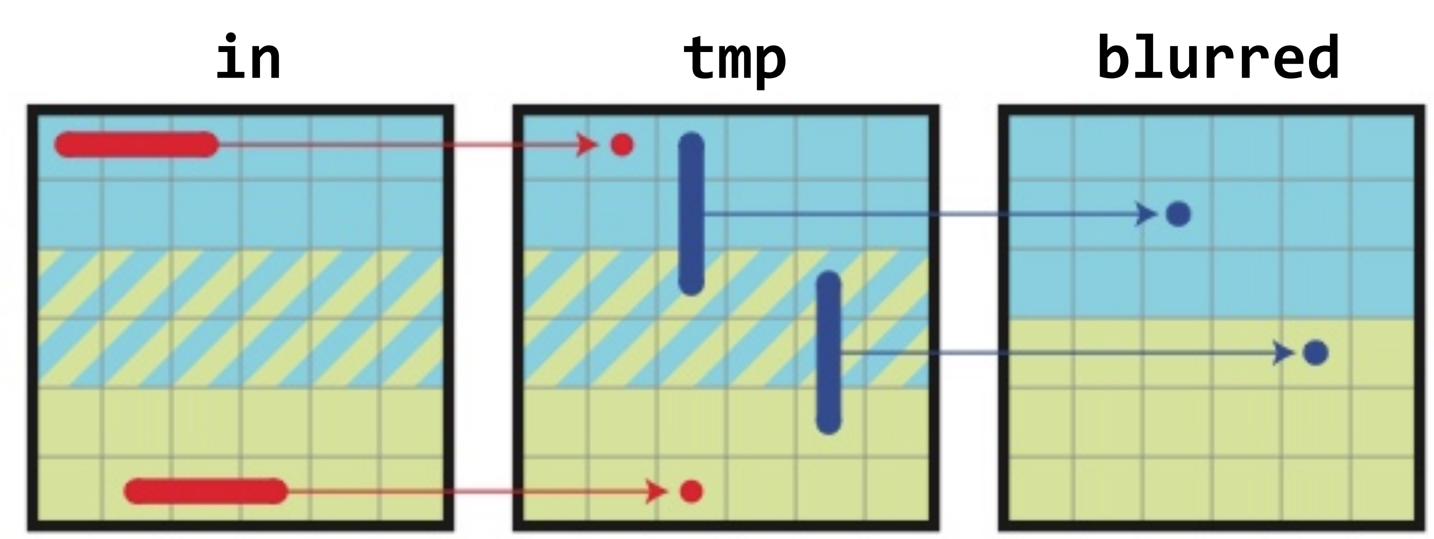
total fusion: values are computed on the fly each time that they are needed.

"Inline"



sliding window: values are computed when needed then stored until not useful anymore.

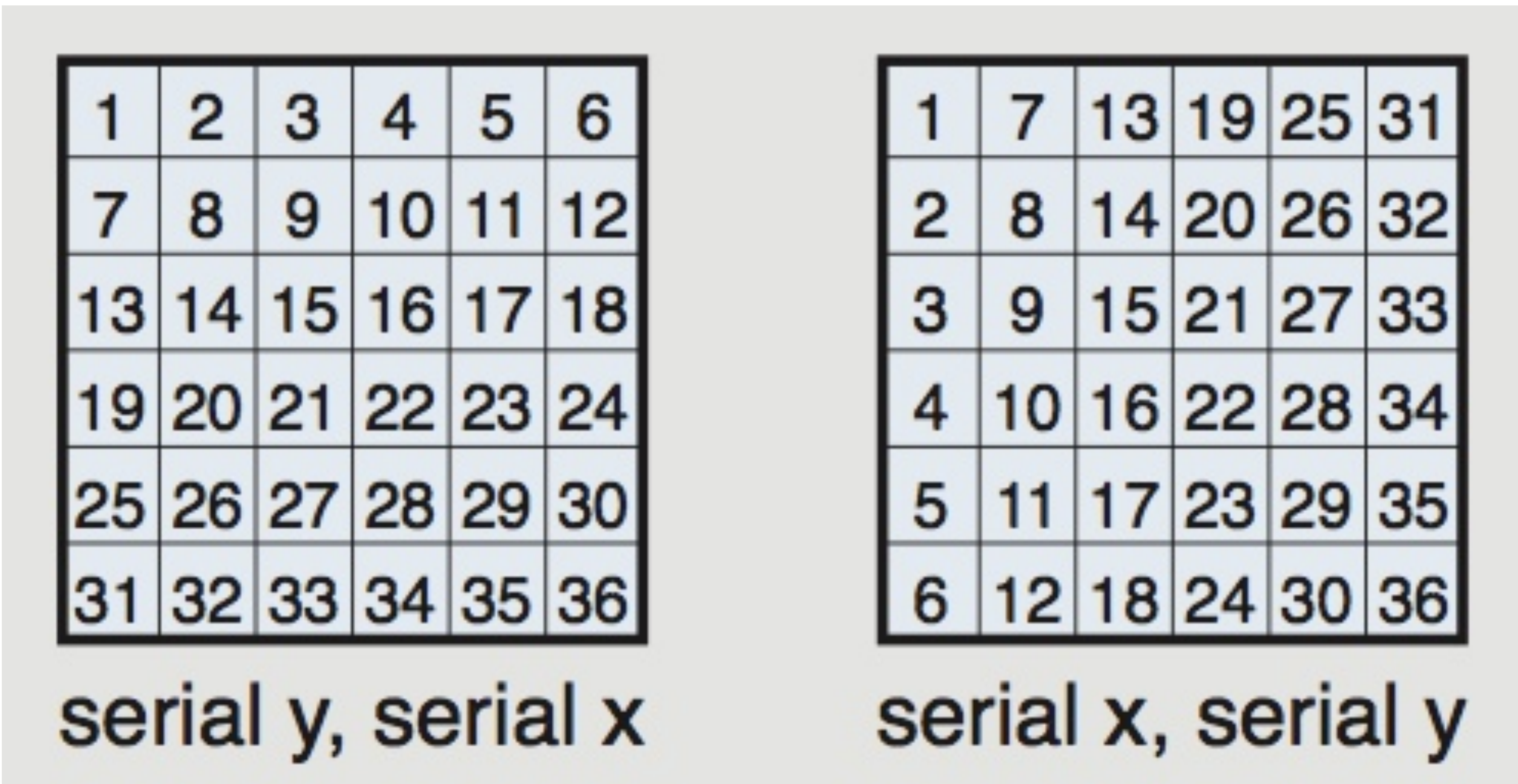
"Sliding Window"



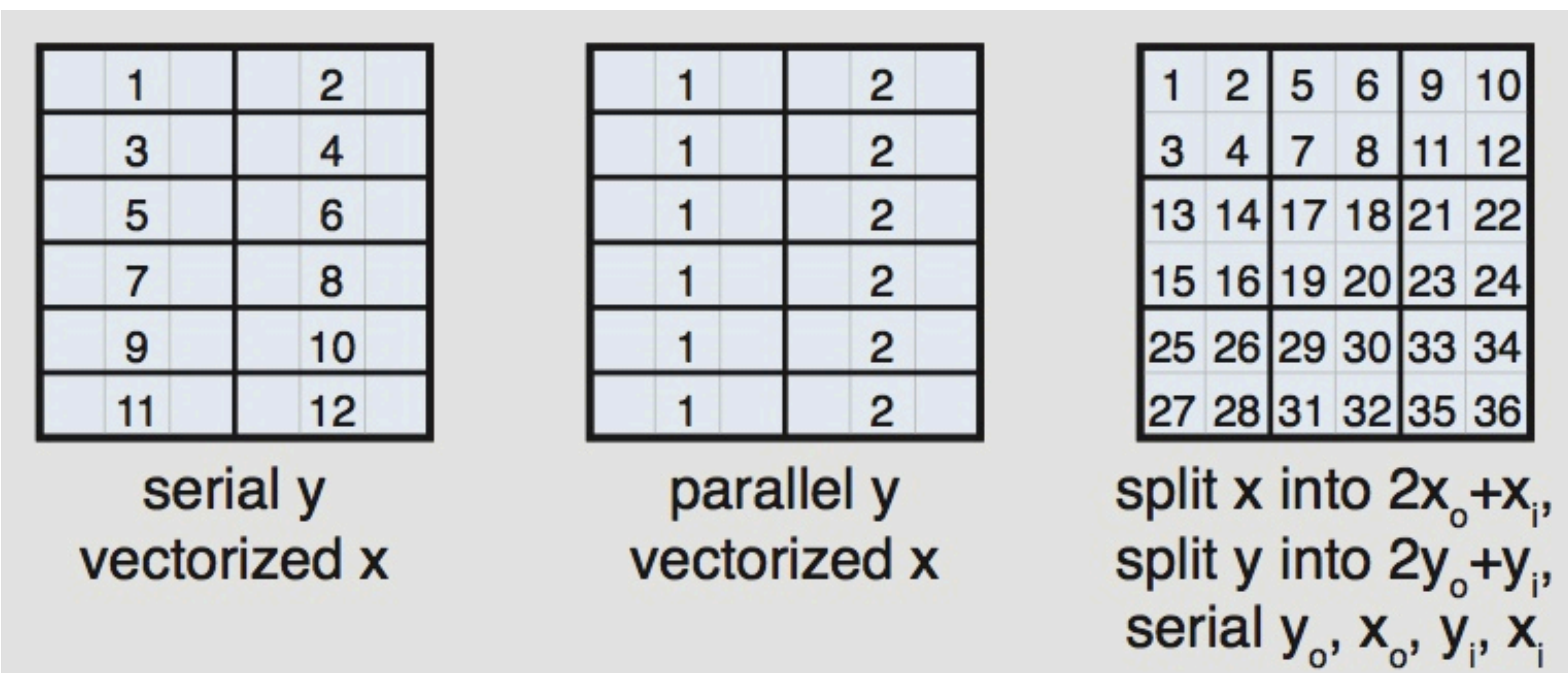
tiles: overlapping regions are processed in parallel, functions are evaluated one after another.

"Chunked"

Halide schedule: domain iteration



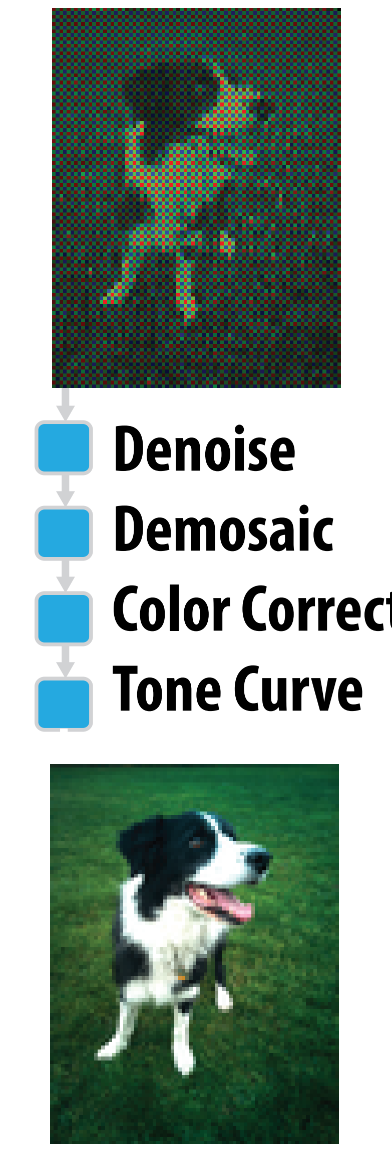
Specify both order and how to parallelize (multi-thread, SIMD vector)



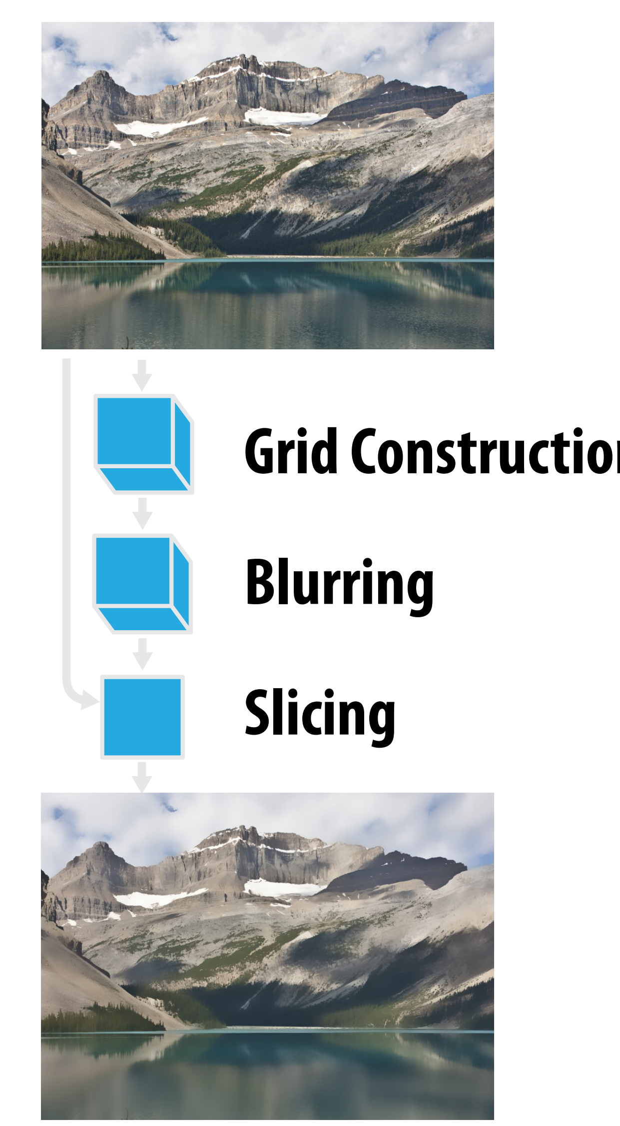
2D blocked iteration order

Halide results

- **Camera RAW processing pipeline**
  (Convert RAW sensor data to RGB image)
  - Original: 463 lines of hand-tuned ARM 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



Takeaway: Halide is not magic, but its abstractions allow rapid exploration of optimization space, allowing programmer to reach optimal points quickly

Summary: image processing basics

- **Same trade-offs arise**
  - Maintain work efficiency
  - Maintain parallelism
  - Achieve bandwidth efficiency (exploit locality when it exists)

- **A well-tuned piece of C code can be an order of magnitude faster than a basic C implementation**
  - A few lines of code turns into many
  - Scheduling decisions not portable across machines (different compute/BW trade-offs, different cache sizes, different instruction sets, specialized HW, ...)

- **Halide is one attempt to raise the level of abstraction**