Lecture 14:

Scheduling Image Processing Pipelines

Visual Computing Systems
CMU 15-869, Fall 2014

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

3x3 box blur (Photoshop)

2X zoom view

2D convolution using 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;
  }
}
```

2D convolution using 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 per image = 9 x WIDTH x HEIGHT

For NxN filter: N^2 x WIDTH x HEIGHT

Two-pass box blur

Total work per image = 6 x WIDTH x HEIGHT

For NxN filter: 2N x WIDTH x HEIGHT

```
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;
  }
}
```

Separable filters

- A <u>separable</u> 2D filter is the outer product of two 1D filters
- Implication:
  - Can implement 2D convolution efficiently as two 1D convolutions

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

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

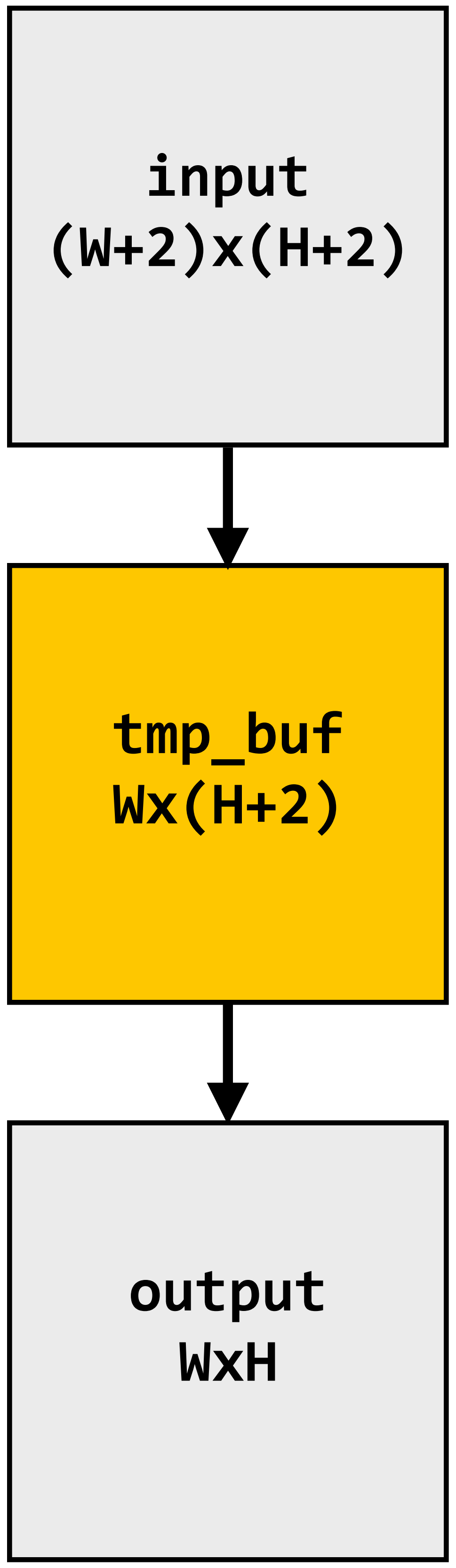
Two-pass box blur

```
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;
  }
}
```

Total work per image = 6 x WIDTH x HEIGHT

For NxN filter: 2N x WIDTH x HEIGHT

But implementation incurs bandwidth cost of writing and reading `tmp_buf`. (and memory 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 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)

Two pass: loads/stores to `tmp_buf` are overhead traffic (this memory traffic is an artifact of the two-pass implementation: it is not intrinsic to computation being performed)

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 <u>three rows of image</u>
- Perfect use of cache lines (don't load unnecessary data into cache)

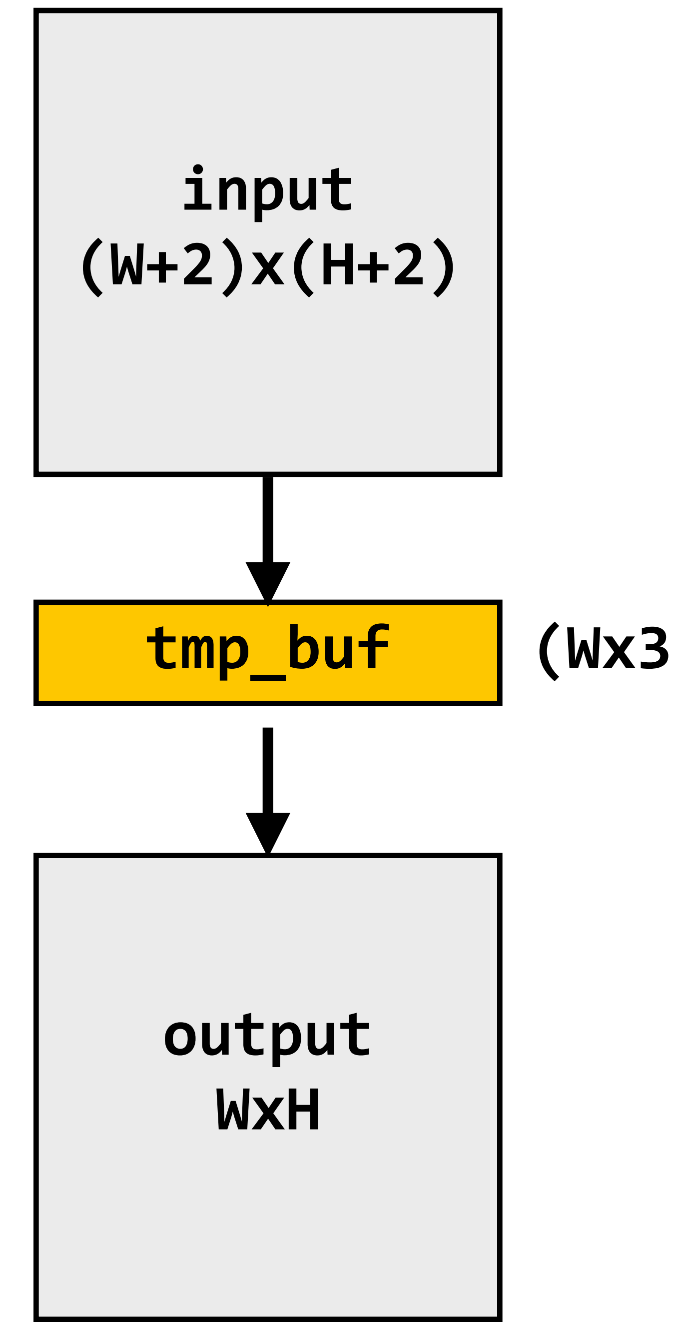
Two-pass image blur, "chunked" (version 1)

```
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;
  }
}
```

Only 3 rows of intermediate buffer needs to be allocated

Produce 3 rows of tmp_buf

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 ????

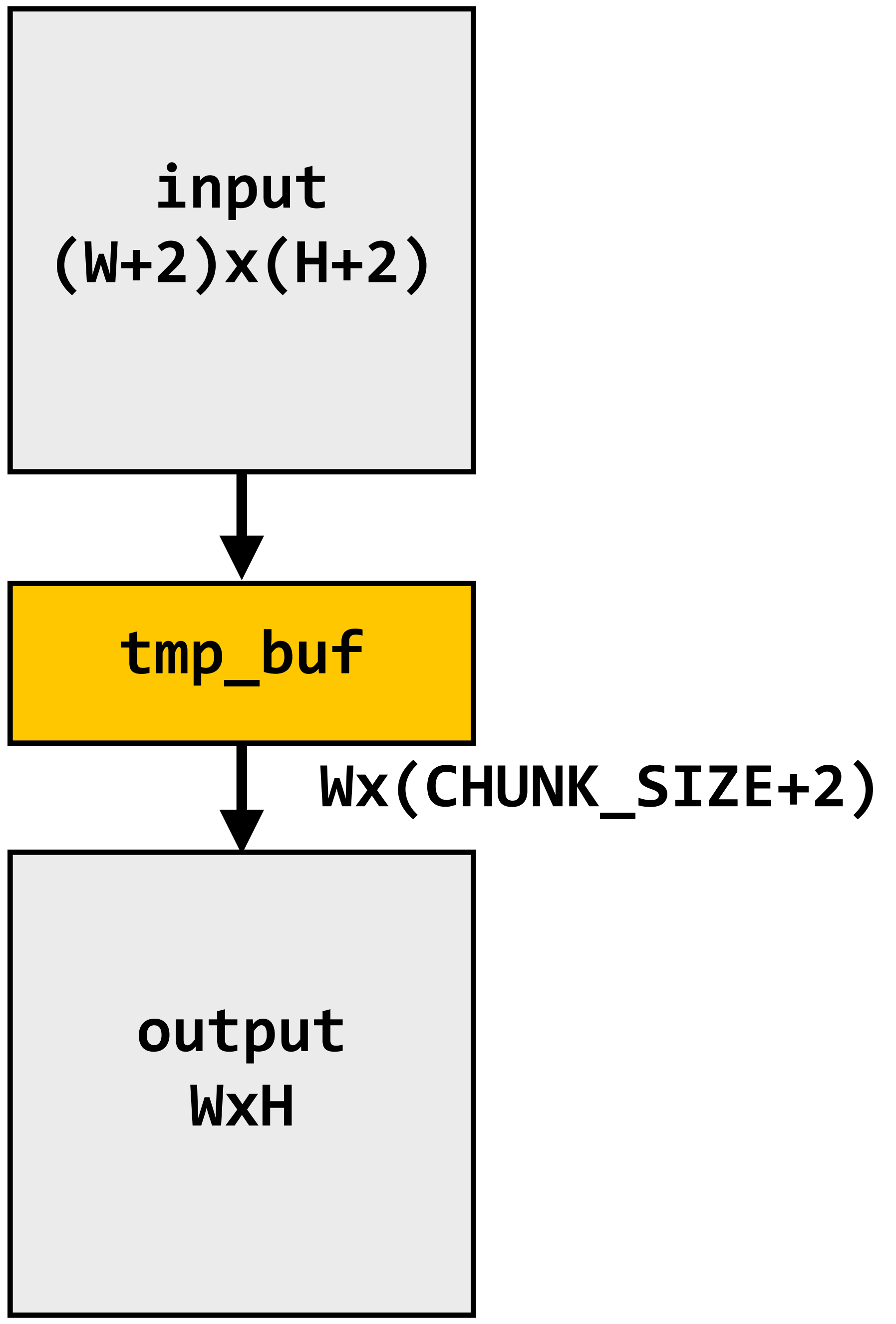
Two-pass image blur, “chunked” (version 2)

```
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+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 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:
(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) x 3 x WIDTH x HEIGHT
= 6.4 x WIDTH x HEIGHT

Trends to idea 6 x WIDTH x HEIGHT as CHUNK_SIZE is increased!

Conflicting goals (once again...)

- **Want to be work efficient (perform fewer operations)**
- **Want to take advantage of locality when present**
  - Ideal: bandwidth cost of implementation is very close to 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
- **Want to execute in parallel (multi-core, SIMD within core)**

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

Halide image processing 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
(Algorithms are image processing pipelines, and a function defines the logic of a pipeline stage)

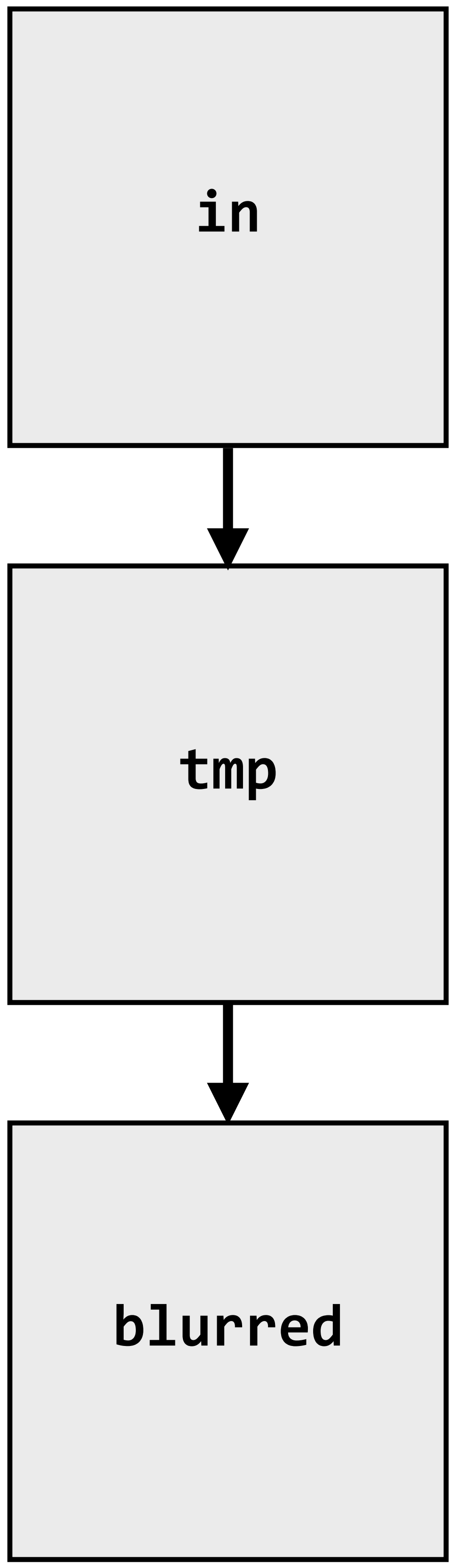
Functions (side-effect-free) map coordinates to values
(`in`, `tmp` and `blurred` are functions)

```
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: Neither execution order of processing nor image storage format is specified by the functional abstraction. The Halide 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

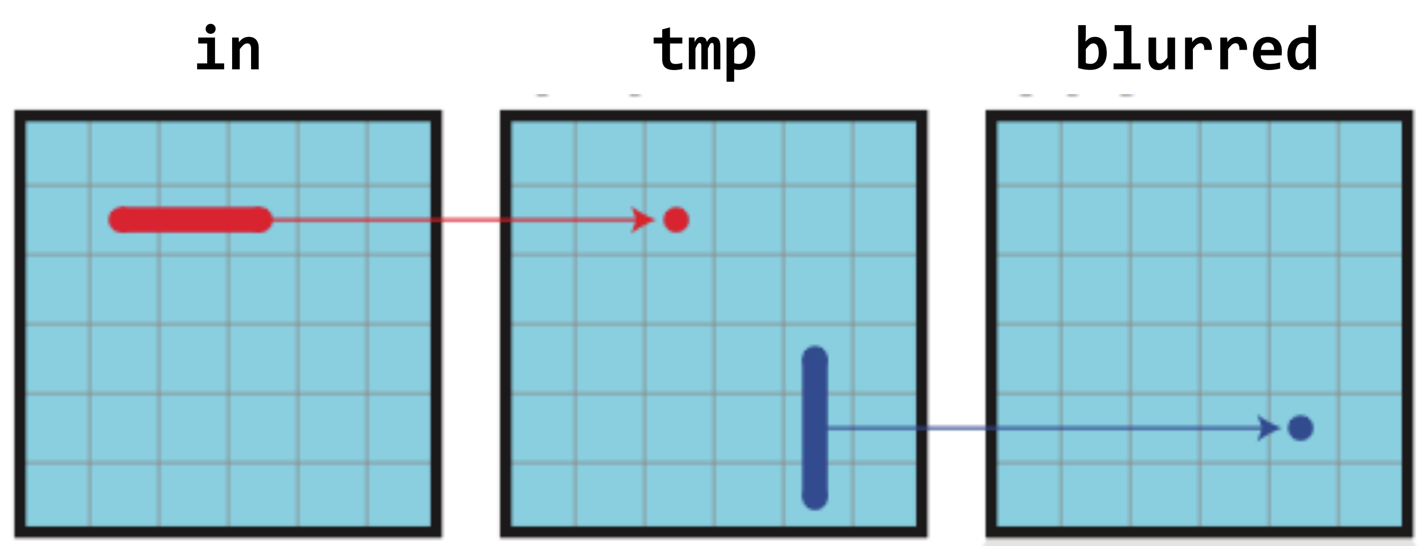
Separation of algorithm from schedule

- Key idea of Halide: a small algebra of composable scheduling operations can describe optimization decisions for a broad class of image processing operations
  - Programmers "optimize" an algorithm by quickly describing a schedule in a domain-specific scheduling co-language.

- Given algorithm + schedule, Halide system generates high-quality code for a target machine
  - Powerful optimizations enabled by limiting scope of application domain:
    - 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

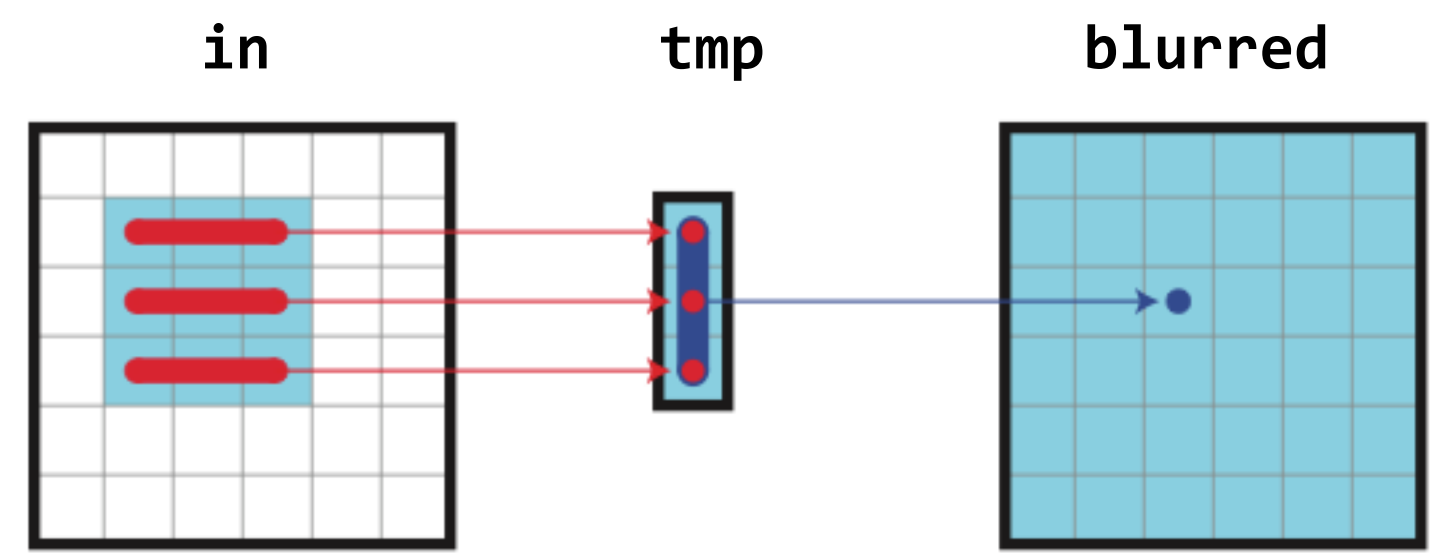
Halide schedule: producer/consumer scheduling

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



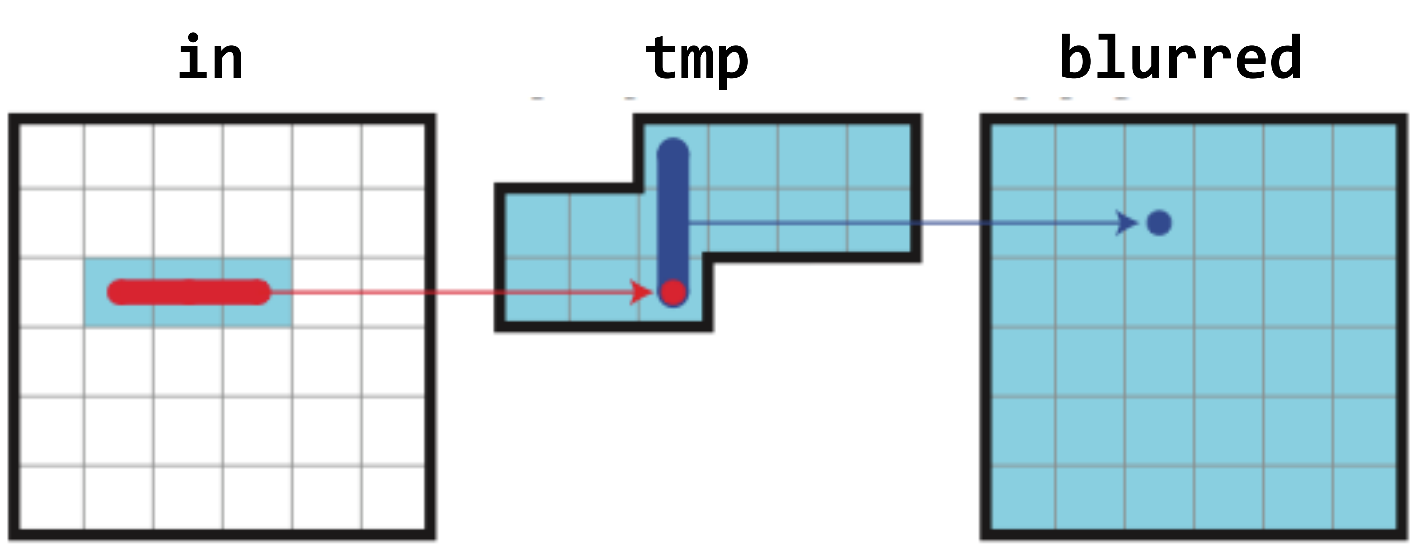
breadth first: each function is entirely evaluated before the next one.

"Root"



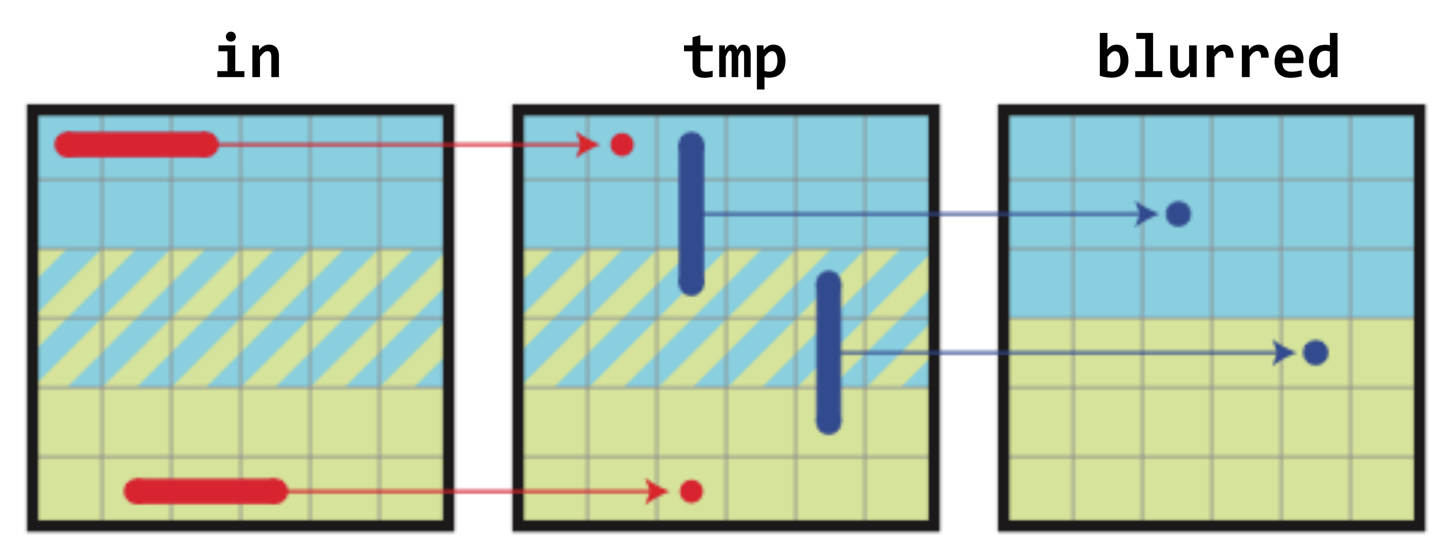
total fusion: values are computed on the fly each time that they are needed.

"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

1	2	3	4	5	6
7	8	9	10	11	12
13	14	15	16	17	18
19	20	21	22	23	24
25	26	27	28	29	30
31	32	33	34	35	36

serial y, serial x

1	7	13	19	25	31
2	8	14	20	26	32
3	9	15	21	27	33
4	10	16	22	28	34
5	11	17	23	29	35
6	12	18	24	30	36

serial x, serial y

Schedule specifies both iteration order and how to parallelize independent iterations (multi-threading, SIMD vector)

1	2
3	4
5	6
7	8
9	10
11	12

serial y
vectorized x

1	2
1	2
1	2
1	2
1	2
1	2

parallel y
vectorized x

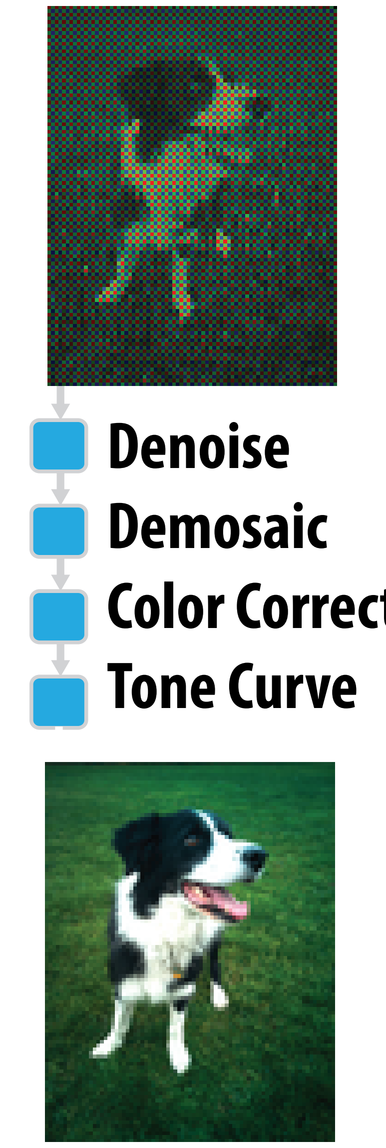
1	2	5	6	9	10
3	4	7	8	11	12
13	14	17	18	21	22
15	16	19	20	23	24
25	26	29	30	33	34
27	28	31	32	35	36

split x into $2x_o+x_i$,
split y into $2y_o+y_i$,
serial y_o, x_o, y_i, x_i

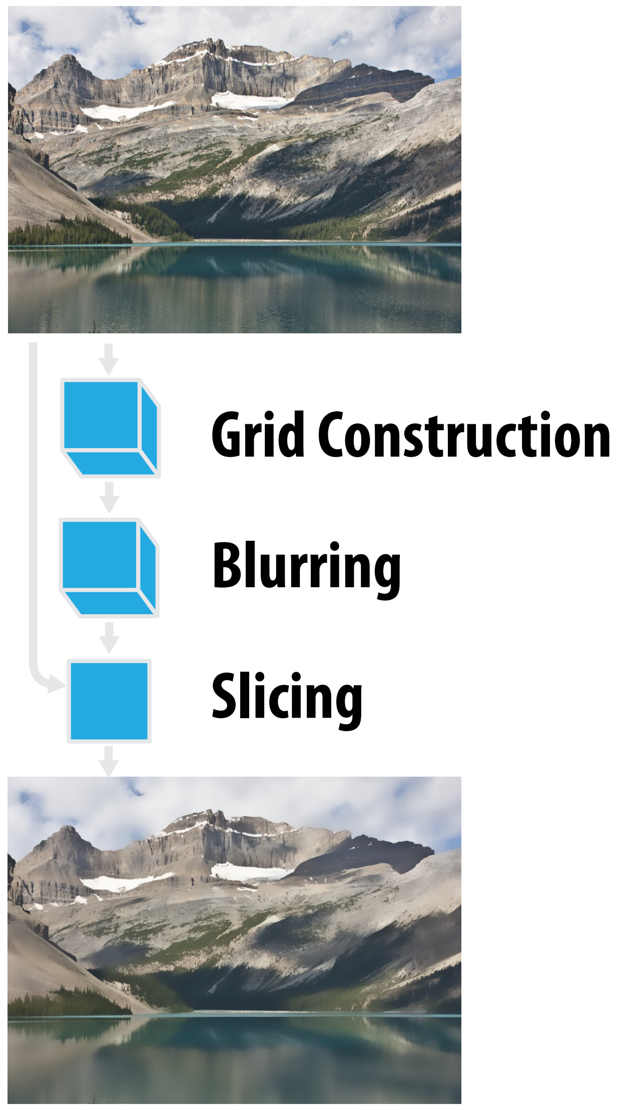
2D blocked iteration order

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 abstractions allow rapid exploration of optimization space, allowing programmer to reach optimal points quickly

Lesson: establishing good abstractions is extremely valuable

- **Halide is one attempt to raise the level of abstraction for authoring image-processing applications**
  - Focus: make is easier for humans to iterate through possible scheduling choices
  - Auto-tuning was explored (see readings) but very long compilation times
  - Other emerging systems with similar goals: See "Darkroom" from readings

- **Halide developed at MIT/Stanford circa 2010-2012**

- **Halide now in use at Google for Android camera processing pipeline**

Summary: image processing basics

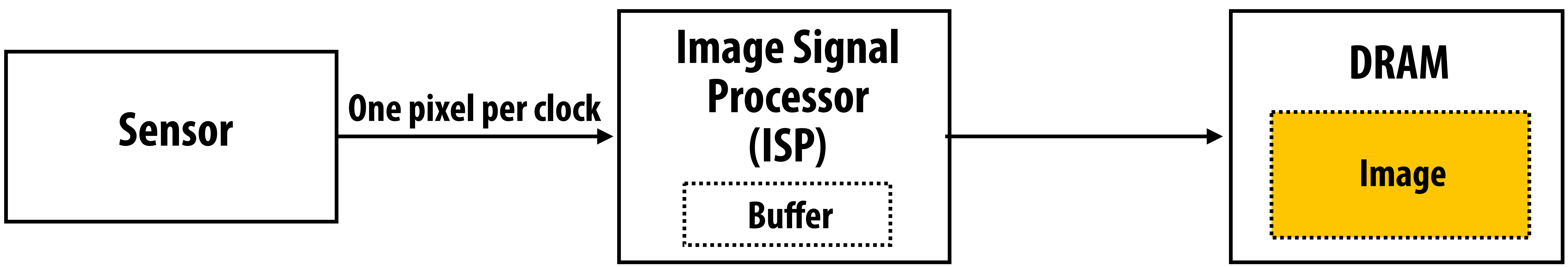
- **Same trade-offs arise as in previous discussions of graphics pipelines**
  - Need to maintain work efficiency
  - Need to achieve bandwidth efficiency (exploit locality when it exists)
  - Need to maintain parallelism

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

Darkroom: efficient programmable image processing from a hardware perspective

Image signal processor

Fixed-function ASIC in modern cameras: responsible for processing RAW pixels to produce output image



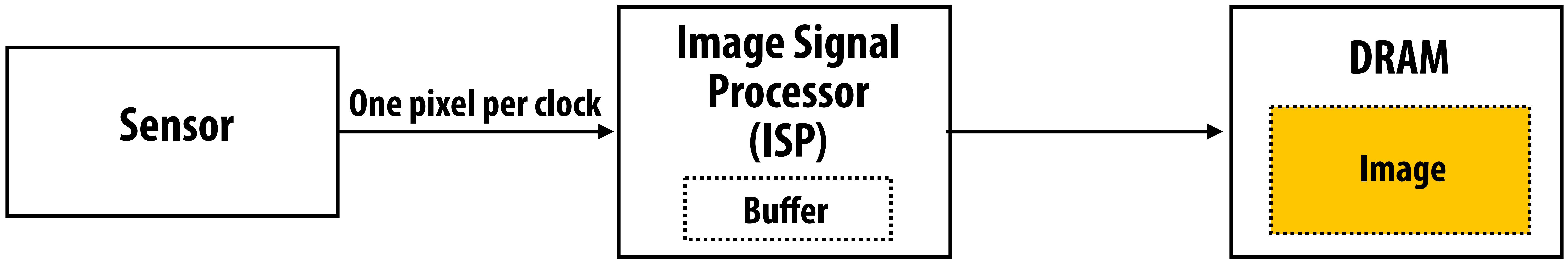
Point-wise operation: one input pixel → one output pixel

```
brighten_image img(x,y) I(x,y) * 1.1
```

Darkroom language syntax

How much buffering is needed in the ISP to implement pointwise operations?

Stencil operations



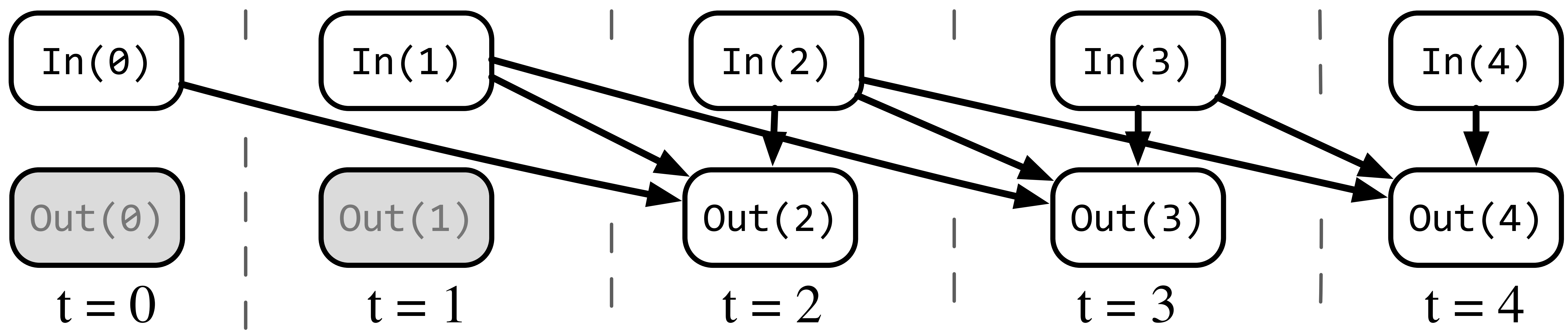
Stencil-operation: local region of input pixels → one output pixel

How much buffering is needed in the ISP to implement this stencil operation?

```
convolve_image_1d img(x,y) (I(x-2,y) + I(x-1,y) + I(x, y)) / 3.0
```

Line-buffered execution

Dependency graph:



ISP "line-buffer" (shift-register) contents:

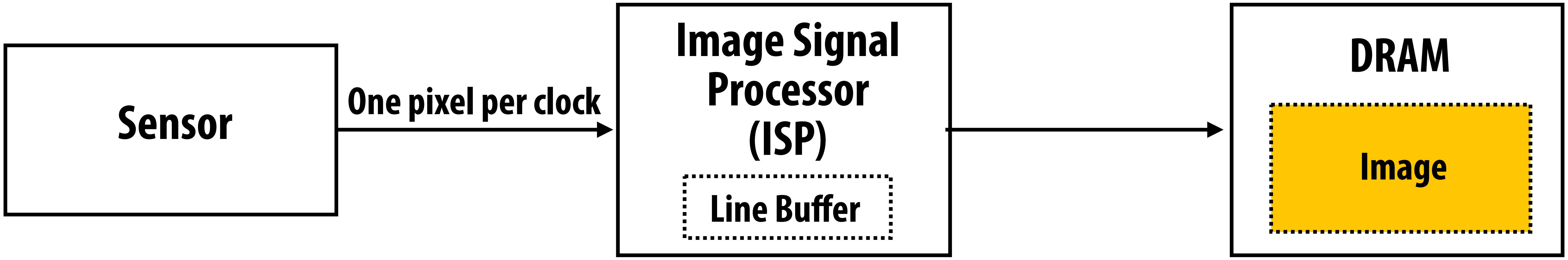
```
t=0:    in(0), __   , __
t=1:    in(1), in(0), __
t=2:    in(2), in(1), in(0)
t=3:    in(3), in(2), in(1)
t=4:    in(4), in(3), in(2)
```

Each clock, ISP performs:

```
out = (line_buffer[0] + line_buffer[1] + line_buffer[2]) / 3.0;
```

Figure credit: Hegarty 2014

Stencil operations



How much buffering is needed in the ISP to implement this stencil operation?

```
convolve_image_2d img(x,y) ((I(x-2,y-2) + I(x-1,y-2) + I(x, y-2) +
                            I(x-2,y-1) + I(x-1,y-1) + I(x, y-1)) +
                            I(x-2,y)   + I(x-1,y)   + I(x, y)) / 9.0;
```

Conversion to 1D problem (assuming image width W):

`I(x + c1, y + c2) = I(x’ + c1 + W*c2)`

where `x’ = y*W + x`

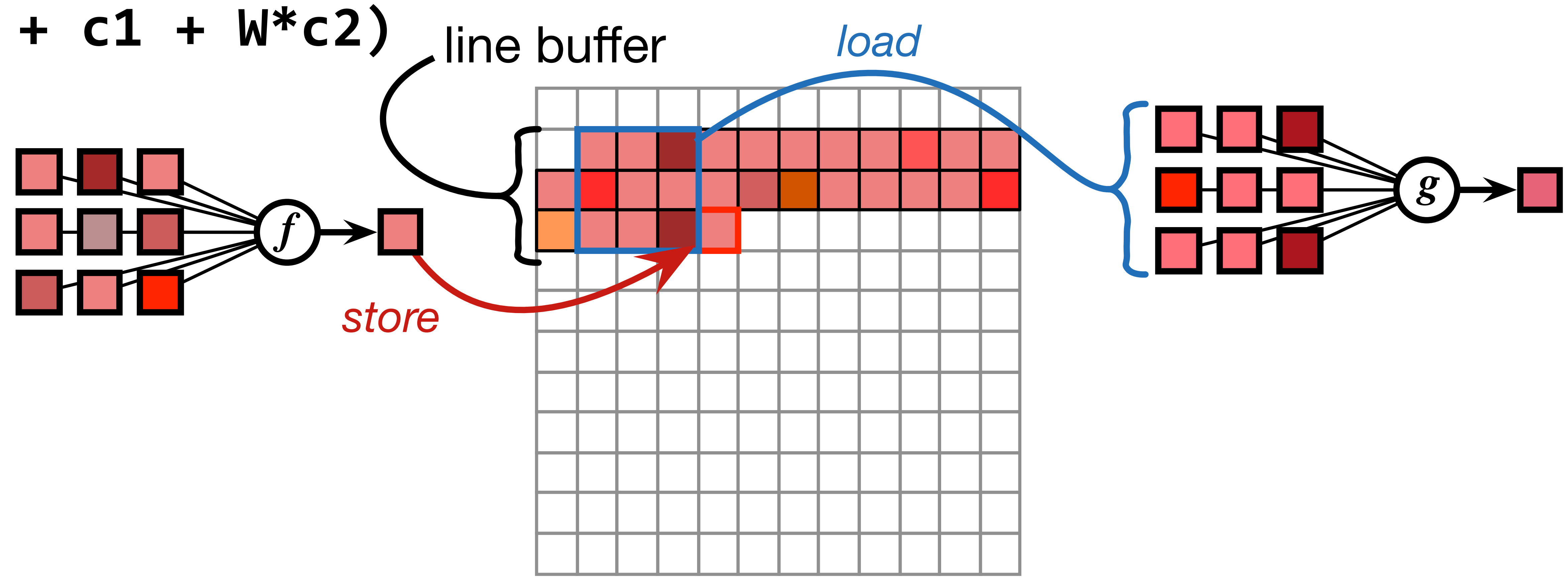


Figure credit: Hegarty 2014

Readings

- *Decoupling Algorithms from Schedules for Easy Optimization of Image Processing Pipelines.* Ragan-Kelly et al. SIGGRAPH 2012

- *Darkroom: Compiling High-Level Image Processing Code into Hardware Pipelines.* Hegarty et al. SIGGRAPH 2014