Lecture 4:

High-performance image processing using Halide

Visual Computing Systems
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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:**
  - Embody the natural way of thinking about a problem

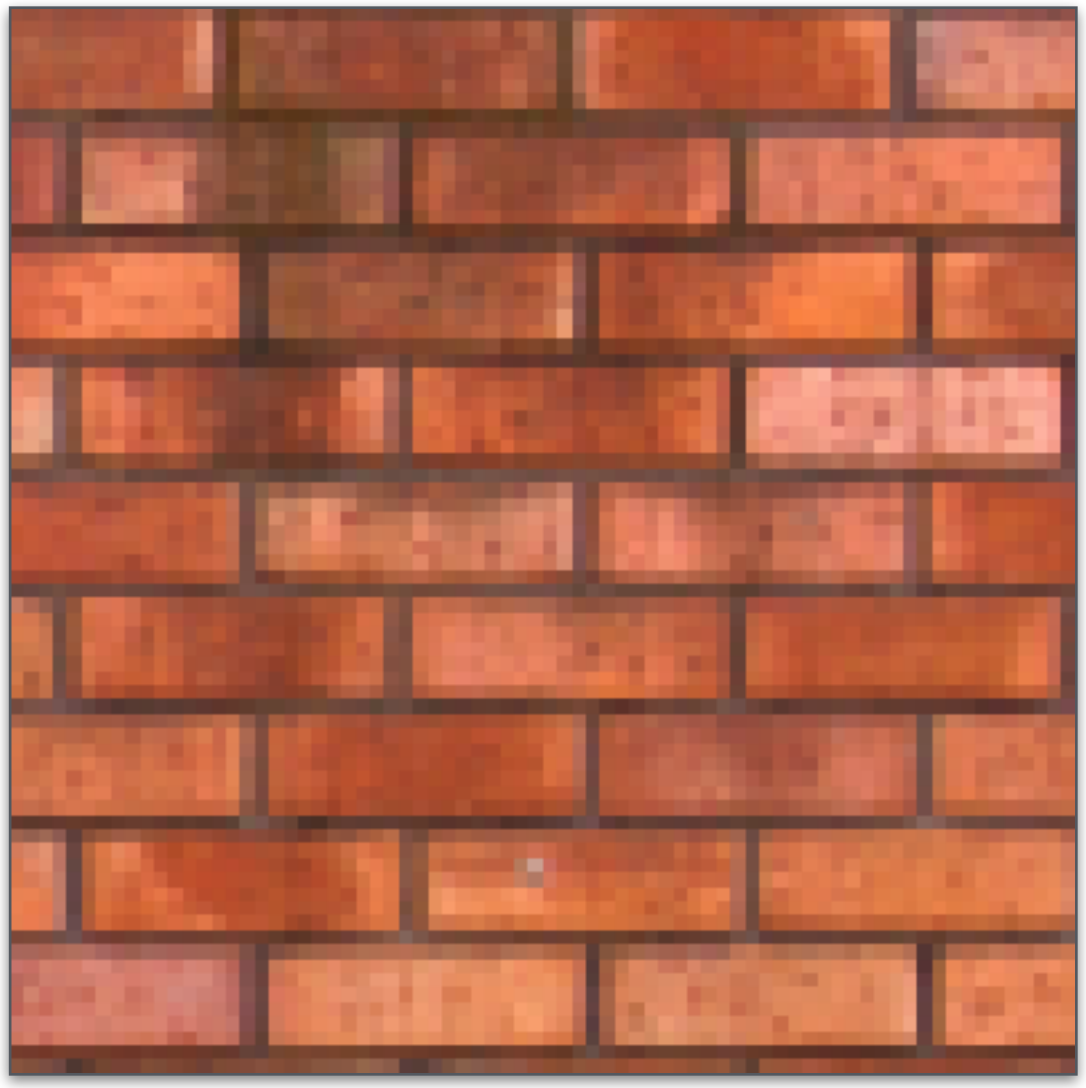
- **Good representations enable the system to provide the application developer useful services:**
  - Validating/providing certain guarantees (correctness, resource bounds, conversation of quantities, type checking)
  - Performance (parallelization, vectorization, use of specialized hardware)
  - Implementations of common, difficult-to-implement functionality (texture mapping and rasterization in 3D graphics, auto-differentiation in ML frameworks)

What does this code do? 🤔😱😩😭

```
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;
   for (int y = 0; y < 32; y++) {
    __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);
}}}}}
```

Example task: sharpen an image

$$\mathbf{F} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



Input

Output

Four different representations of sharpen

1

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

2

$$F=\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

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

3

```
Image input;
Image output;
output[i][j]
    = F[0][0] * input[i-1][j-1] +
      F[0][1] * input[i-1][j]   +
      F[0][2] * input[i-1][j+1] +
      F[1][0] * input[i][j-1]   +
      F[1][1] * input[i][j]     +
      ...
```

4

```
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;
  }
}
```

More image processing tasks from last lecture

Sobel Edge Detection

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * I$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * I$$

$$G = \sqrt{{G_x}^2 + {G_y}^2}$$

3x3 Gaussian blur

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

2x2 downsample (via averaging)

```
output[x][y] = (input[2x][2y]   + input[2x+1][2y] +
                input[2x][2y+1] + input[2x+1][2y+1]) / 4.f;
```

Gamma Correction

```
output[x][y] = pow(input[x][y], 0.5f);
```

LUT-based correction

```
output[x][y] = lookup_table[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);
```

Histogram

```
bin[input[x][y]]++;
```

Image processing workload characteristics

- Sequences of operations on images
- Natural to think about algorithms in terms of their local behavior: “pointwise code”: output at pixel (x,y) is function of input pixels in neighborhood around (x,y)
- Common case: access to local "window” of pixels around a point
- But some algorithms require data-dependent data access (e.g., data-dependent access to lookup-tables)
- Multiple rates of computation (upsampling/downsampling)
- Simple inter-pixel communication/reductions (e.g., building a histogram, computing maximum brightness pixel)

Halide language

[Ragan-Kelley 2012]

Simple language embedded in C++ for describing sequences of image processing operations (image processing pipelines)

Functions map integer coordinates to values (e.g., colors of corresponding pixels)

```
Var x, y;
Func blurx, blury, 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,y));
blury(x,y) = 1/3.f * (blurx(x,y-1) + blurx(x,y+1) + blurx(x,y+1));

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

// execute pipeline on domain of size 800x600
Image<uint8_t> result = out.realize(800, 600);
```

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**
- **Halide expression: a side-effect free expression describes how to compute a function's value at a point in it's domain in terms of the values of other functions.**

Halide language

Update definitions modify function values

Reduction domains provide the ability to iterate

```
Var x;
Func histogram, modified;
Image<uint8_t> in = load_image("myimage.jpg");

modified(x,y) = in(x,y) + 10;
modified(x,3) *= 2;  // update definition, modifies 3rd row
modified(3,y) *= 2;  // update definition, modifies 3rd column

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

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

// update definition on histogram
// for all points in domain, increment appropriate bin
histogram(in(r.x, r.y)) += 1;

Image<int> result = histogram.realize(256);
```

Key aspects of Halide's design

- Adopts local "pointwise" view of expressing algorithms
- Language is highly constrained so that iteration over domain points is implicit (no explicit loops in Halide)
  - Halide language is declarative. It does not define order of iteration, or what values in domain or stored!
  - It only defines what operations are needed to compute these values.

```
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,y));
out(x,y) =   1/3.f * (blurx(x,y-1) + blurx(x,y+1) + blurx(x,y+1));

// execute pipeline on domain of size 800x600
Image<uint8_t> result = our.realize(800, 600);
```

Efficiently executing Halide programs

Example

Consider writing code for the 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,y));
out(x,y) = 1/3.f * (blurx(x,y-1) + blurx(x,y+1) + blurx(x,y+1));

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

Two-pass 3x3 blur

Total work per image = 6 x WIDTH x HEIGHT

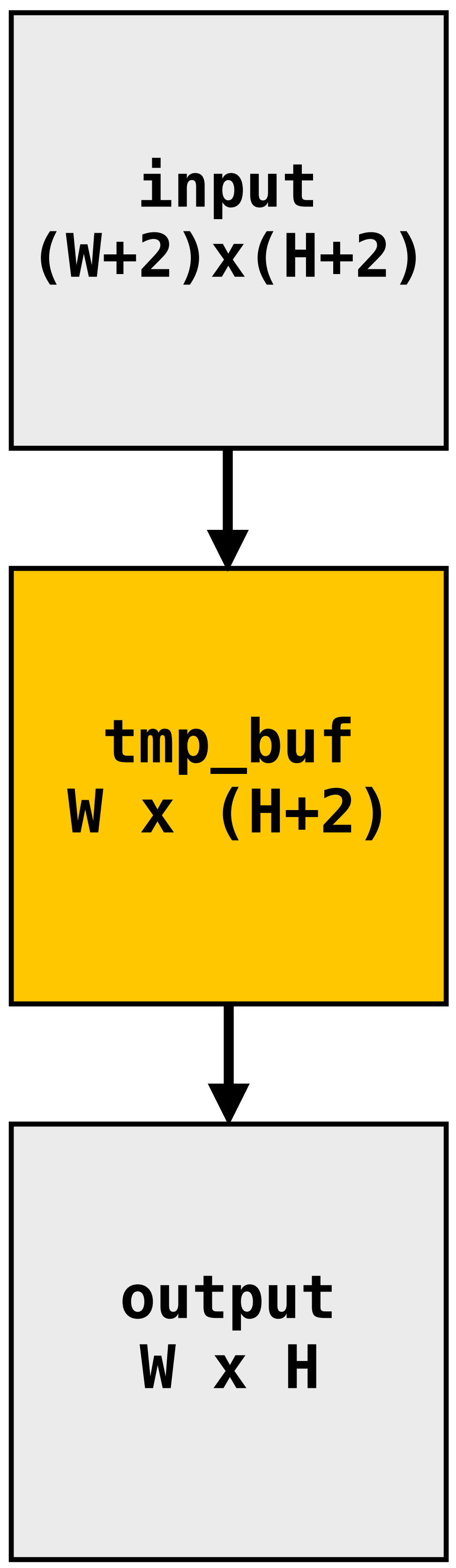
For NxN filter: 2N x WIDTH x HEIGHT

WIDTH x HEIGHT extra storage

```
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;
  }
}
```

1D horizontal blur

1D vertical blur



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)**

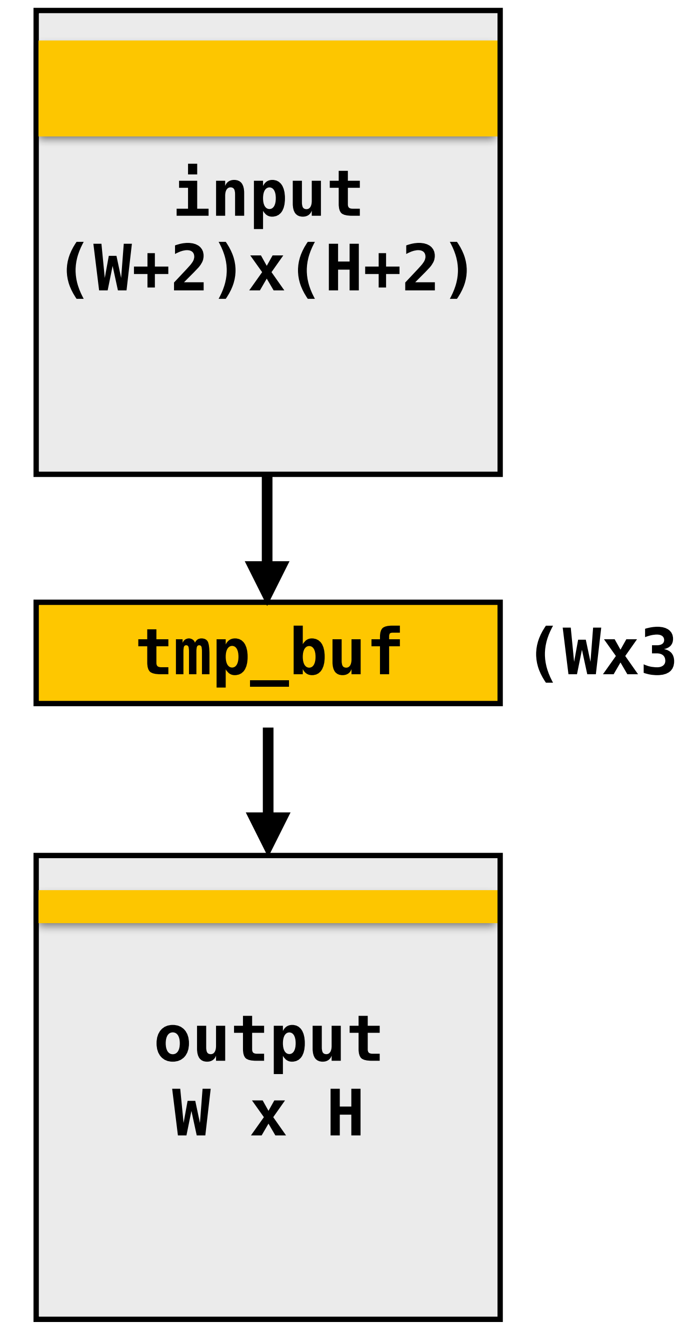
Two pass: loads/stores to `tmp_buf` are overhead (this memory traffic is an artifact of the two-pass implementation: it is not intrinsic to computation being performed)

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[] = {1.0/3, 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)

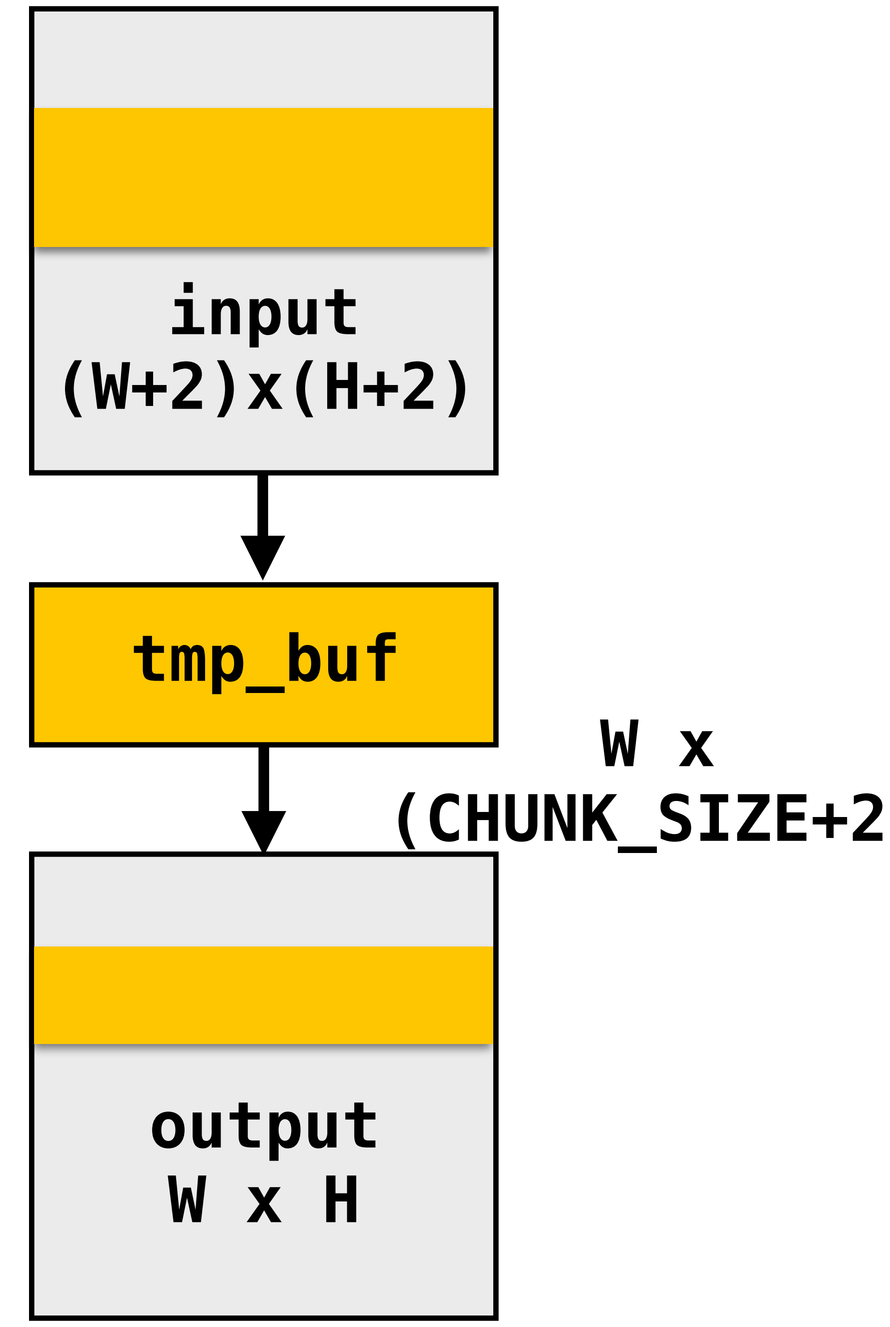
Two-pass image blur, "chunked" (version 2)

```
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) 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!

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 implementation

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 tiled iteration (to maximize cache hit rate)

use of SIMD vector intrinsics

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

Image processing pipelines feature complex sequences of functions

Benchmark	Number of Halide functions
Two-pass blur	2
Unsharp mask	9
Harris Corner detection	13
Camera RAW processing	30
Non-local means denoising	13
Max-brightness filter	9
Multi-scale interpolation	52
Local-laplacian filter	103
Synthetic depth-of-field	74
Bilateral filter	8
Histogram equalization	7
VGG-16 deep network eval	64

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”

```
Func blurx, out;
Var  x, y, xi, yi;
Image<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);
```

When evaluating `out`, 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

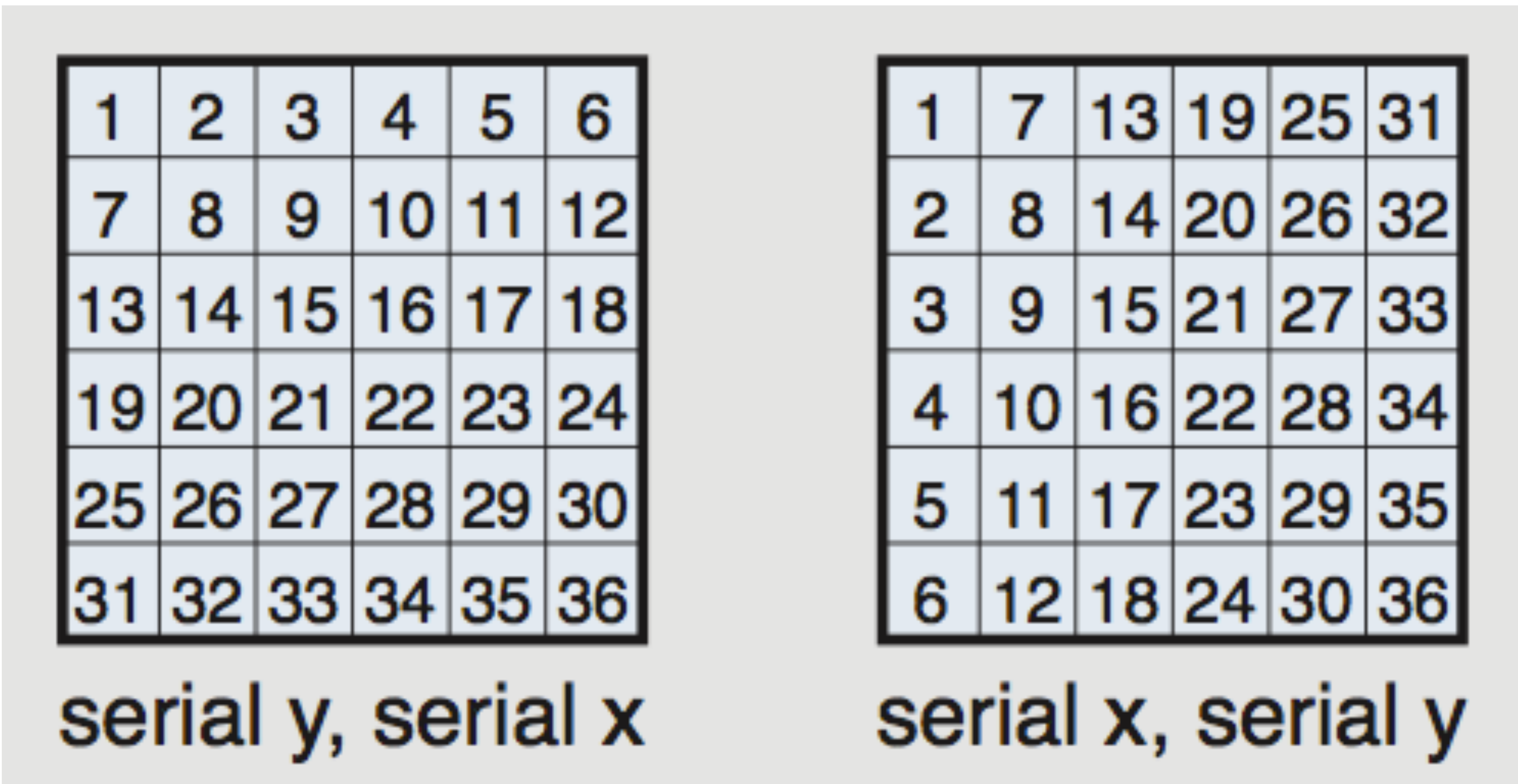
Produce elements `blurx` on demand for each tile of output. Vectorize the x (innermost) loop

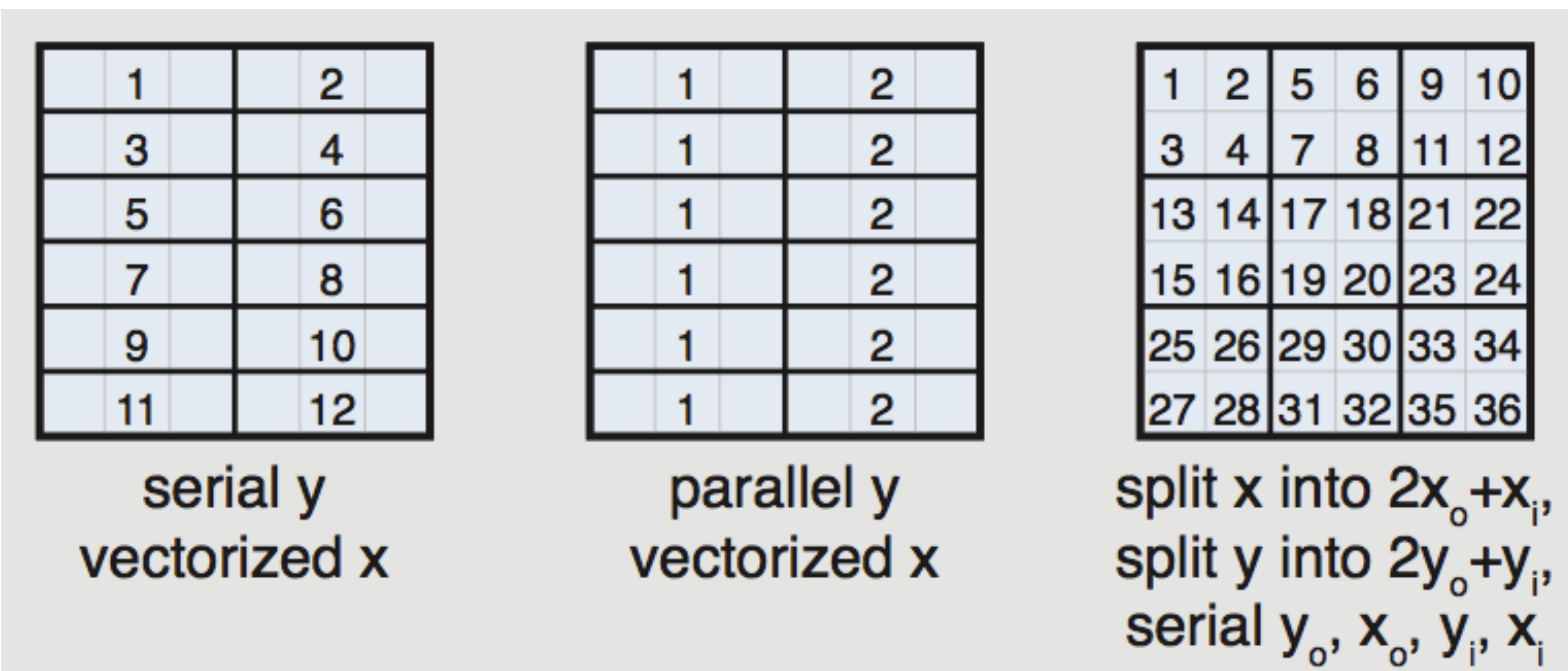
```
// execute pipeline on domain of size 1024x1024
Image<uint8_t> result = out.realize(1024, 1024);
```

Scheduling primitives allow the programmer to specify a global “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

```
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;
```

Given this schedule for the function "out"...

```
out.tile(x, y, xi, yi, 256, 32).vectorize(xi,8).parallel(y);
```

Halide compiler will generate this parallel, vectorized loop nest for computing elements of `out`...

```
for y=0 to num_tiles_y:      // parallelize this loop over multiple threads
   for x=0 to num_tiles_x:
      for yi=0 to 32:
         for xi=0 to 256:    // vectorize this loop with SIMD instructions
            idx_x = x*256+xi;
            idx_y = y*32+yi
            out(idx_y, idx_y) = …
```

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_root();
```

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

```
allocate buffer for all of blur(x,y)
for y=0 to HEIGHT:
  for x=0 to WIDTH:
     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
            out(idx_y, idx_y) = …
```

all of blurx is computed here

values of blurx consumed 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(x_i);
```

Compute necessary elements of blurx within out's xi loop nest

```
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 blurx

            // compute 3 elements of blurx needed for out(idx_x, idx_y) here
            out(idx_y, idx_y) = …
```

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(x);
```

Compute necessary elements of blurx within out's x loop nest (all necessary elements for one tile of out)

```
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:
            blur(xi,yi) = // 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_y, idx_y) = …
```

tile of blurx is computed here

tile of blurx is consumed here

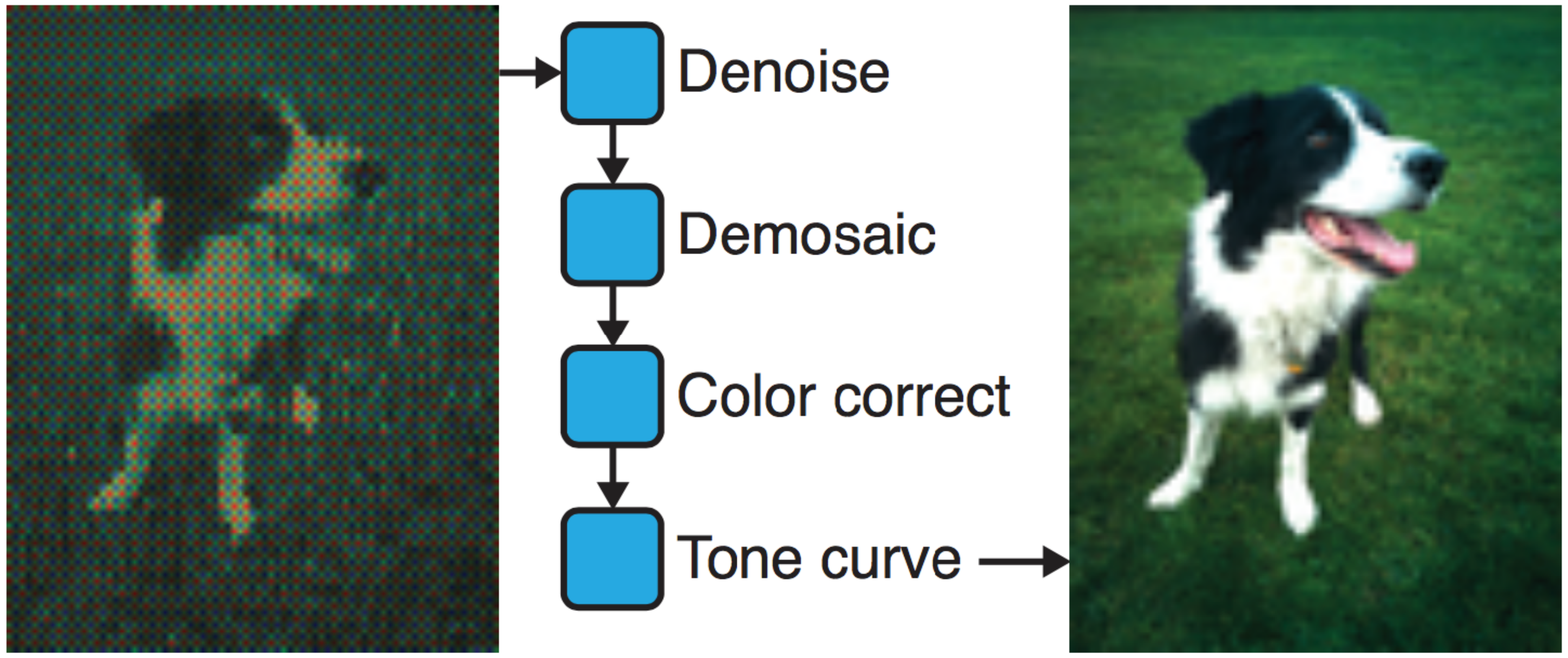
Halide: two domain-specific co-languages

- Functional primitives for describing image processing operations
- Additional primitives for describing schedules
- Design principle: separate "algorithm specification" from schedule
  - Programmer's responsibility: provide a high-performance schedule
  - Compiler's responsibility: carry out mechanical process of generating threads, SIMD instructions, managing buffers, etc.
  - Result: enable programmer to rapidly exploration of space of schedules ("tile these loops", vectorize this loop", "parallelize this loop across cores")
- Application domain scope:
  - All computation on regular N-D coordinate spaces
  - Only feed-forward pipelines (includes special support for reductions and fixed recursion depth)
  - All dependencies inferable by compiler

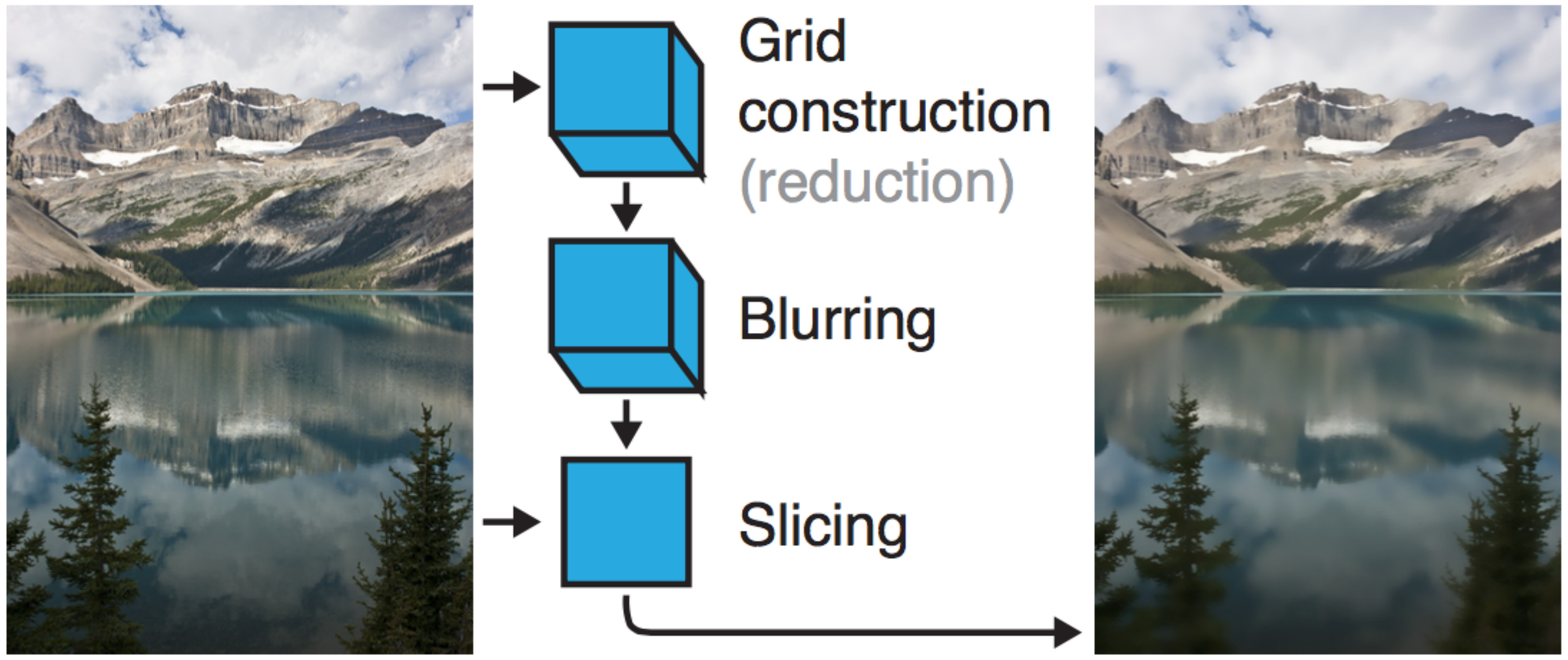
Initial Halide results

[Ragan-Kelley 2012]

- **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

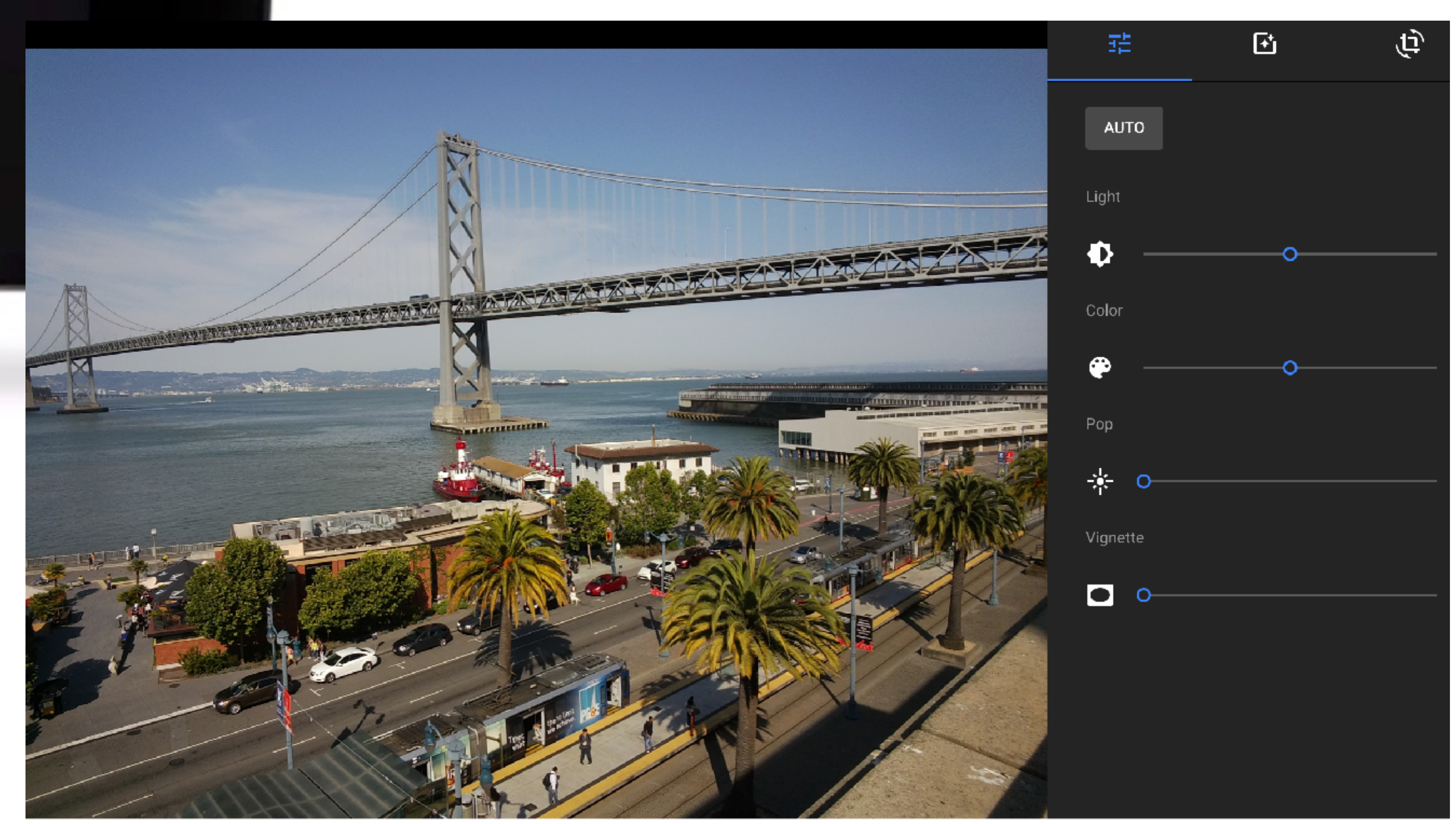


- **Bilateral filter**
  (Common image filtering operation used in many applications)
  - Original 122 lines of C++
  - Halide: 34 lines algorithm + 6 lines schedule
    - CPU implementation: 5.9x faster
    - GPU implementation: 2x faster than hand-written CUDA



Halide used in practice

- Halide used to implement Google Pixel Photos app
- Halide code used to process images uploaded to Googl



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 primitives for a programmer (that has strong knowledge of code optimization, such as a 15-418 student) to rapidly express what optimizations the system should apply
  - Halide compiler carries out the nitty-gritty of mapping that strategy to a machine

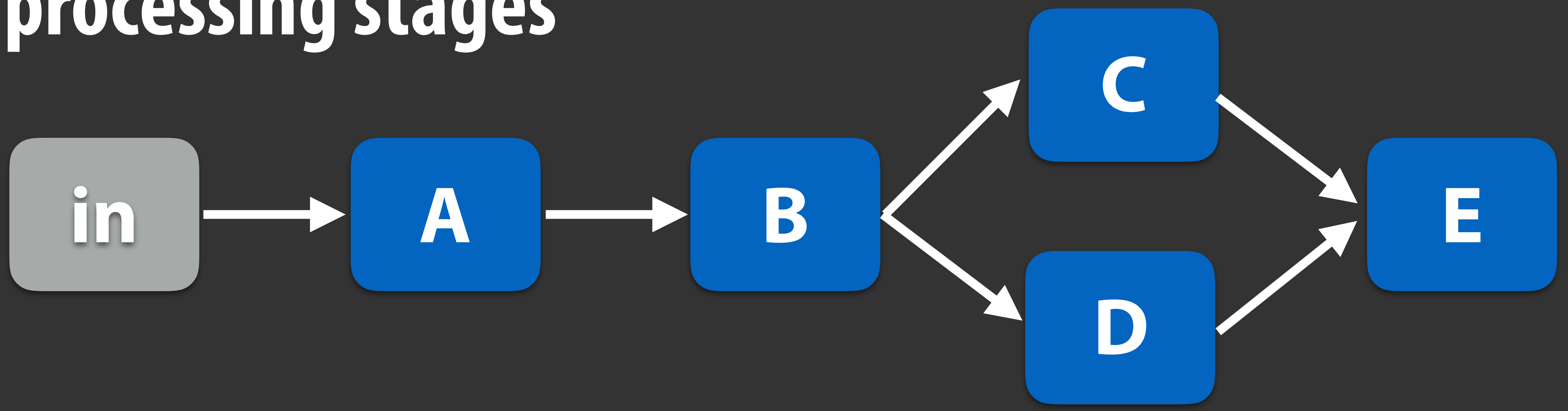
Automatically generating Halide schedules

- **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 [Mullapudi 2016]**

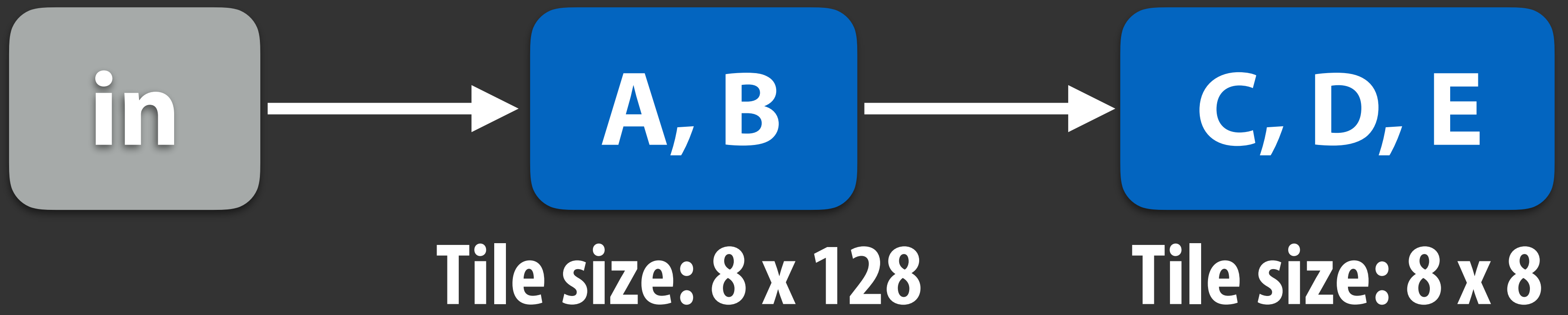
Problem definition

Input: DAG of image processing stages

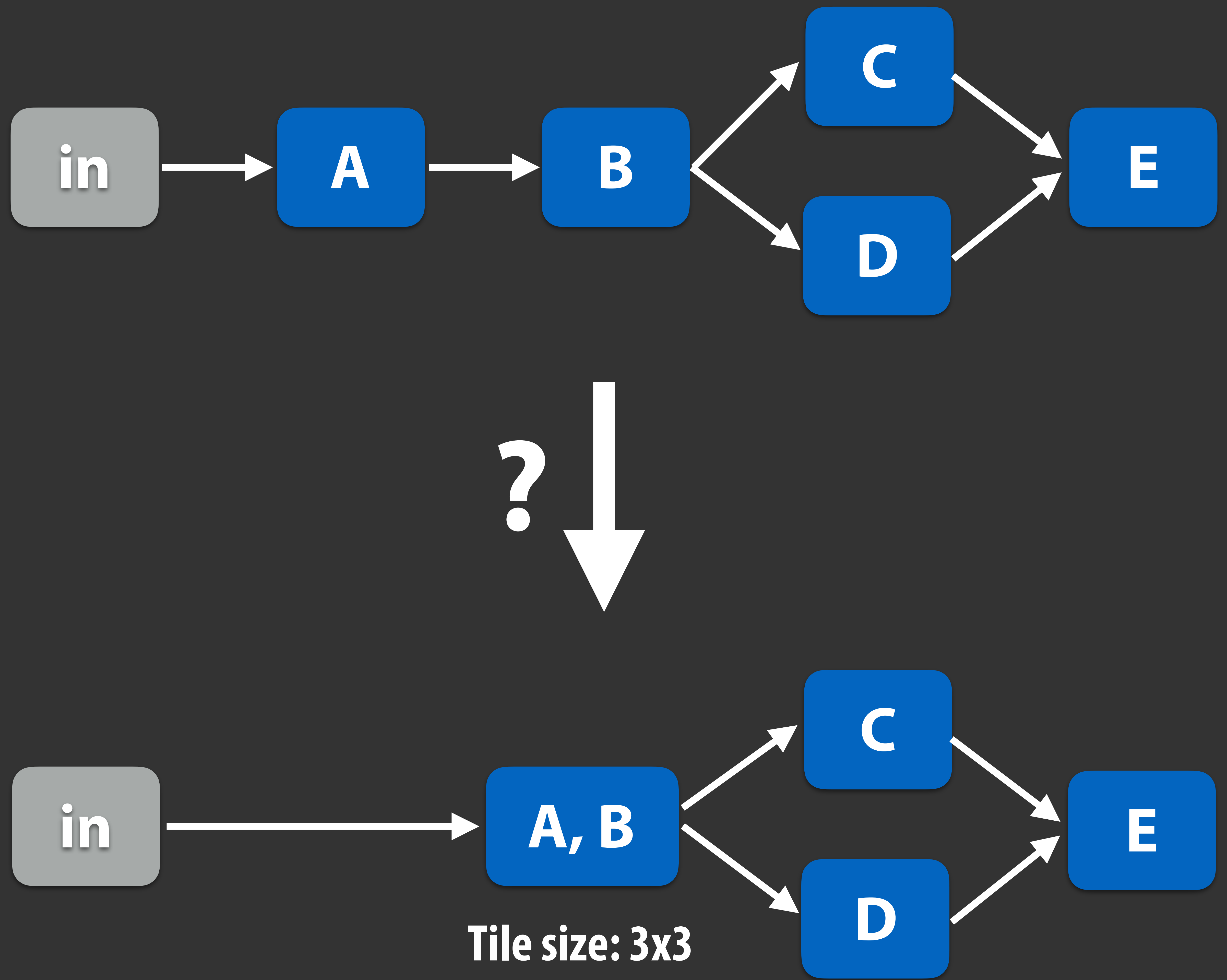


Output: optimized schedule

```
for each 8x128 tile in parallel
    compute required pixels of A
    compute pixels in tile of B

for each 8x8 tile in parallel
    compute required pixels of C
    compute required pixels of D
    compute pixels in tile of E
```



How to tile a group



The autoscheduler fits programs to a single schedule template

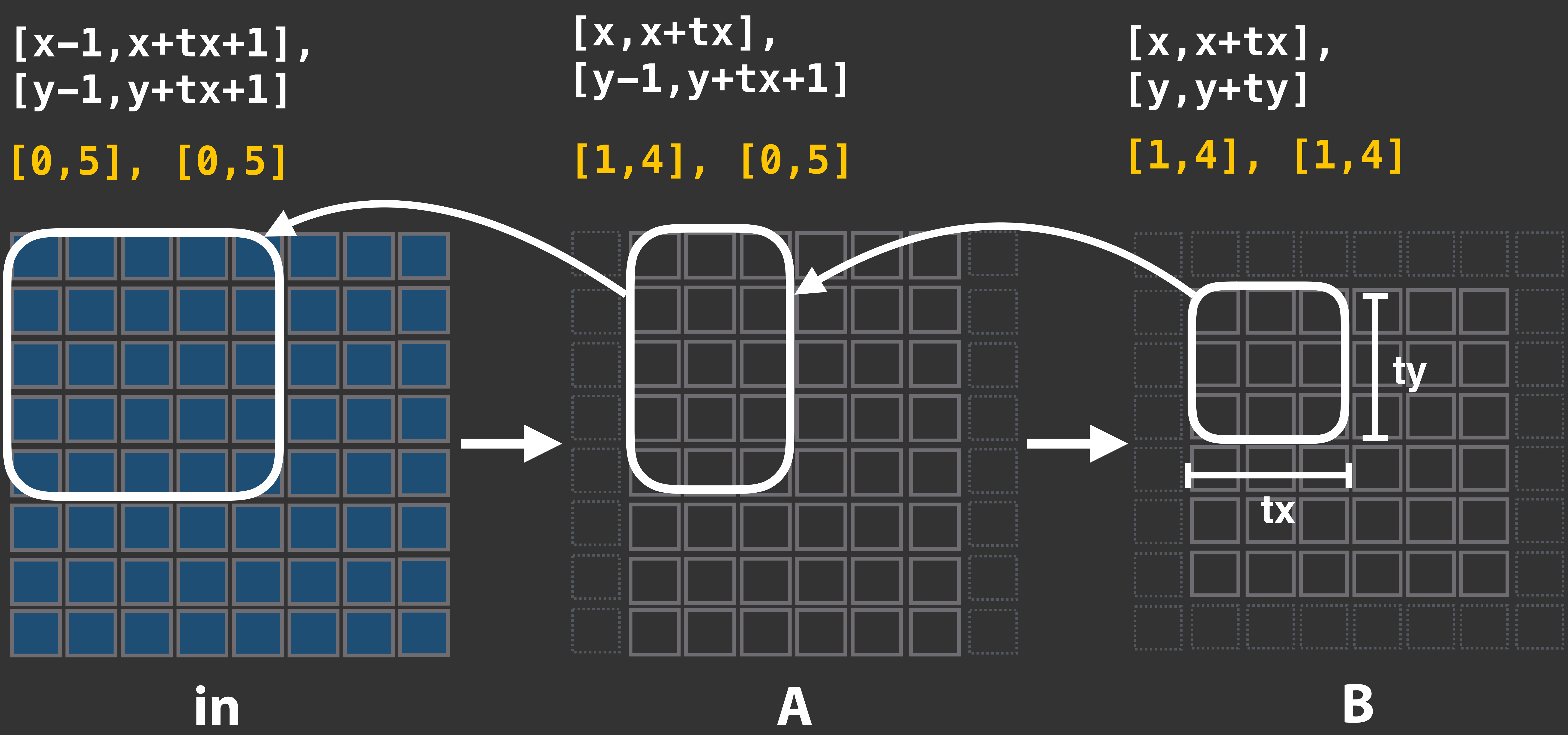
For a single sub-DAG

```
for each tile_y:  // multi-core parallel
   for each tile_x: // multi-core parallel

       allocate tmpC; // buffer for C for tile
       allocate tmpD; // buffer for D for tile

       for each y in required region of C
          for each x in required region of C
             tmpC = ....  // DRAM accesses to B

       for each y in required region of D
          for each x in required region of D
             tmpD = .... // DRAM accessed to B

      for each y in tile:
         for each x in tile: // optionally SIMD vector parallel

             x' = tile_x * TILE_WIDTH + x;
             y' = tile_y * TILE_HEIGHT + y;
             E(x',y') = ...
```

Cost model to evaluate a tiling:

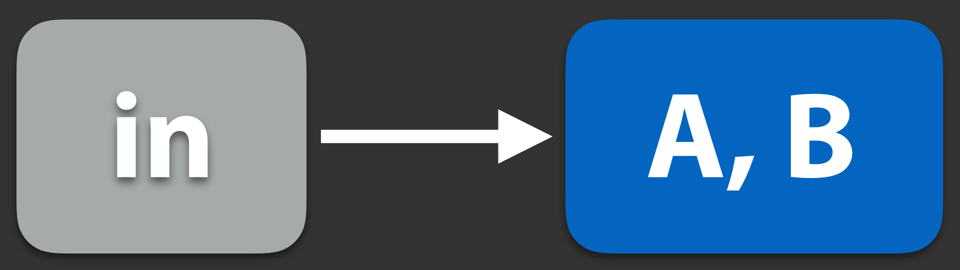
- cost of data access is proportional to buffer size
- cost arithmetic op = 1

Estimating costs via interval analysis

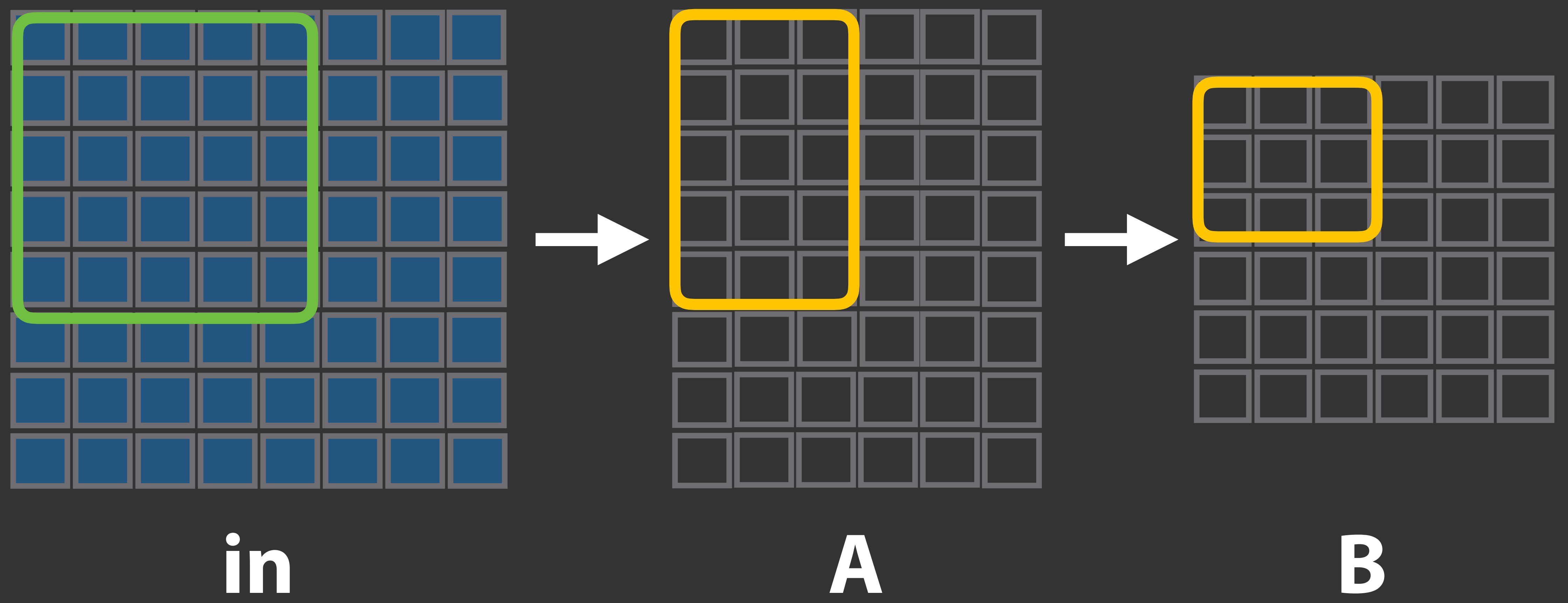



```
A(x,y)   = in(x−1,y) + in(x,y) + in(x+1,y)
B(x,y)   = A(x,y−1)  + A(x,y)  + A(x,y+1)
```

Estimating costs via interval analysis

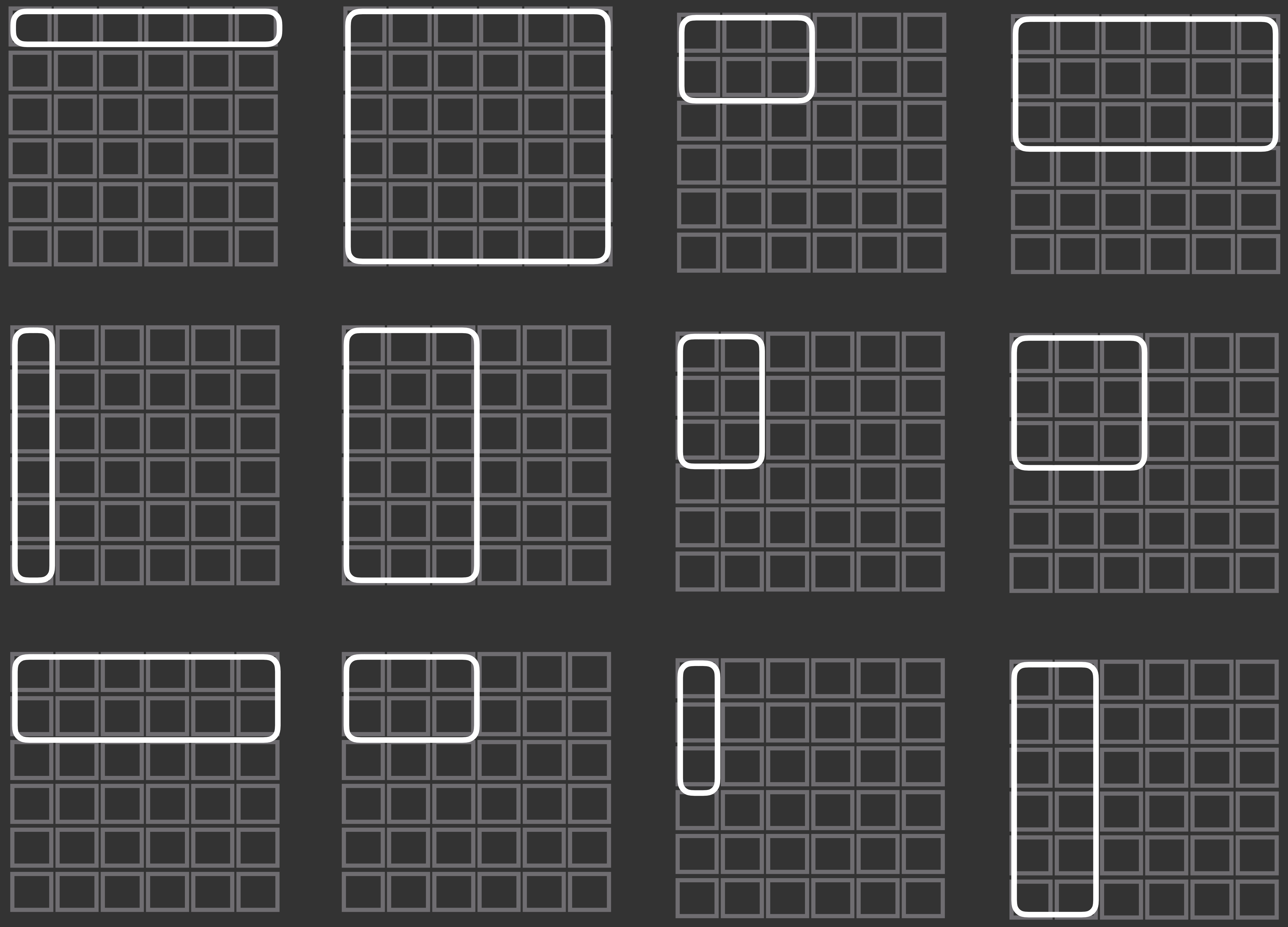


Tile size: 3x3

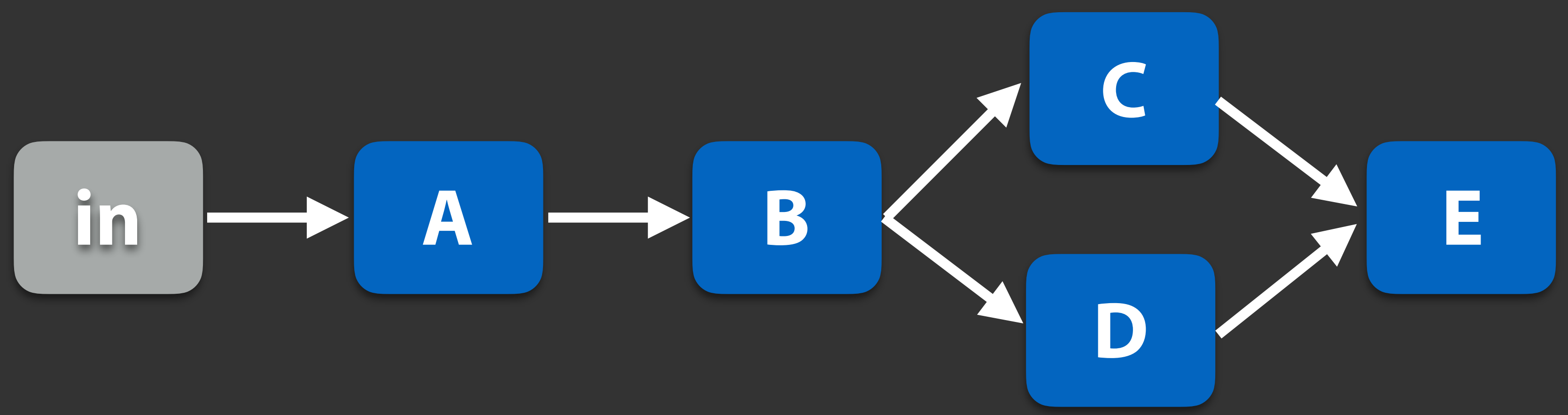


Cost = Number of arithmetic operations +
Number of memory accesses x COST OF ELEMENT LOAD

Search for most efficient tile size



Finding efficient groupings



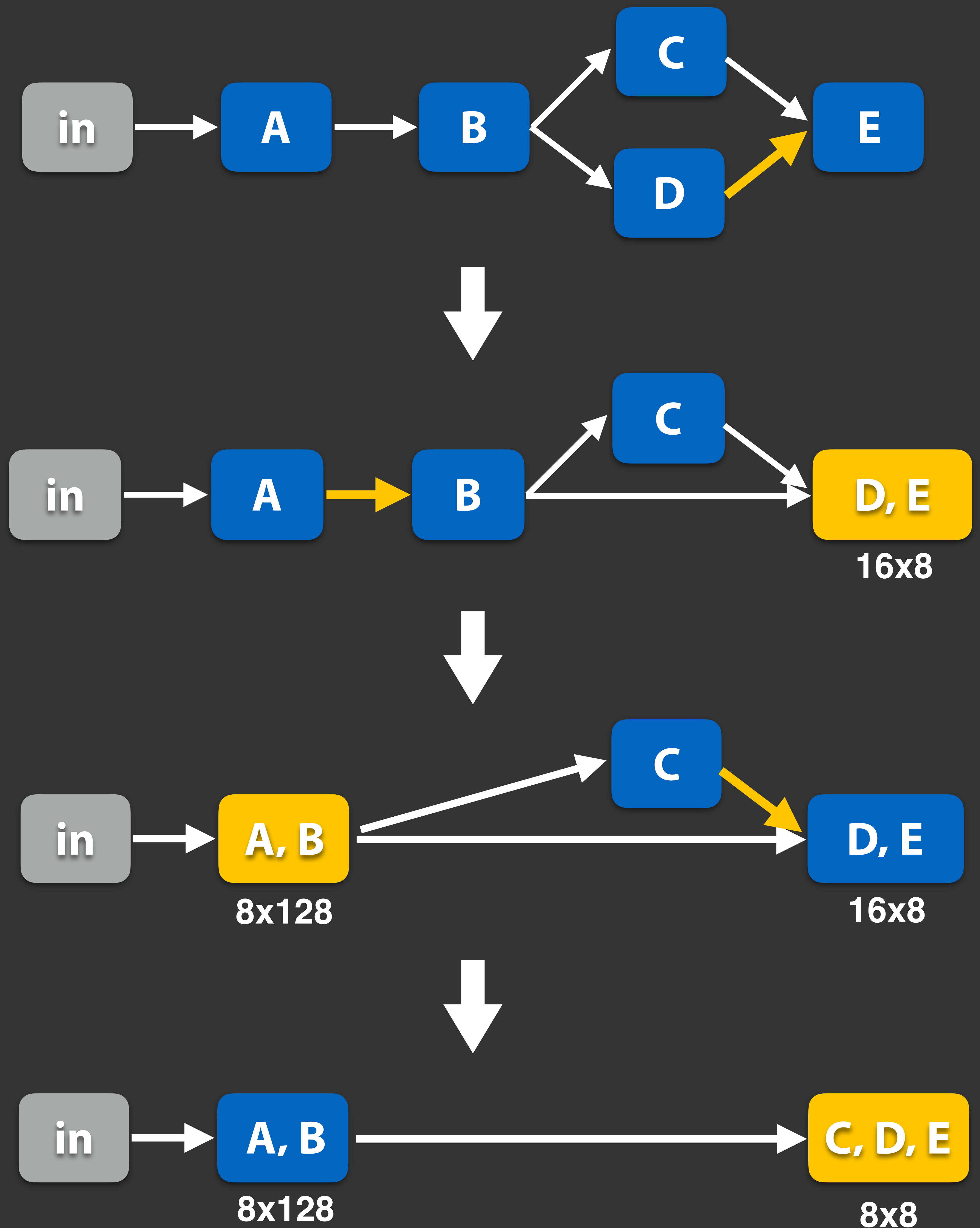
Given the ability to compute a good tiling of groups…

Which stages should be grouped together?

Greedy grouping strategy

Greedily form groups (take best merge)

But re-evaluate local optimization to determine tile size each step.



for each 8x128 tile
    compute required pixels of A
    compute required pixels of B
    compute pixels in tile of D

for each 8x8 tile
    compute required pixels of C
    compute pixels in tile of E

Complete schedule

Add standard compiler optimizations: multi-core parallelism, vectorization, loop unrolling, etc.

```
for each 8x128 tile in parallel
    vectorize compute required pixels of A unroll x by 4
    vectorize compute required pixels of B
    vectorize compute pixels in tile of D

for each 8x8 tile in parallel
    vectorize compute required pixels of C unroll y by 2
    vectorize compute pixels in tile of E
```

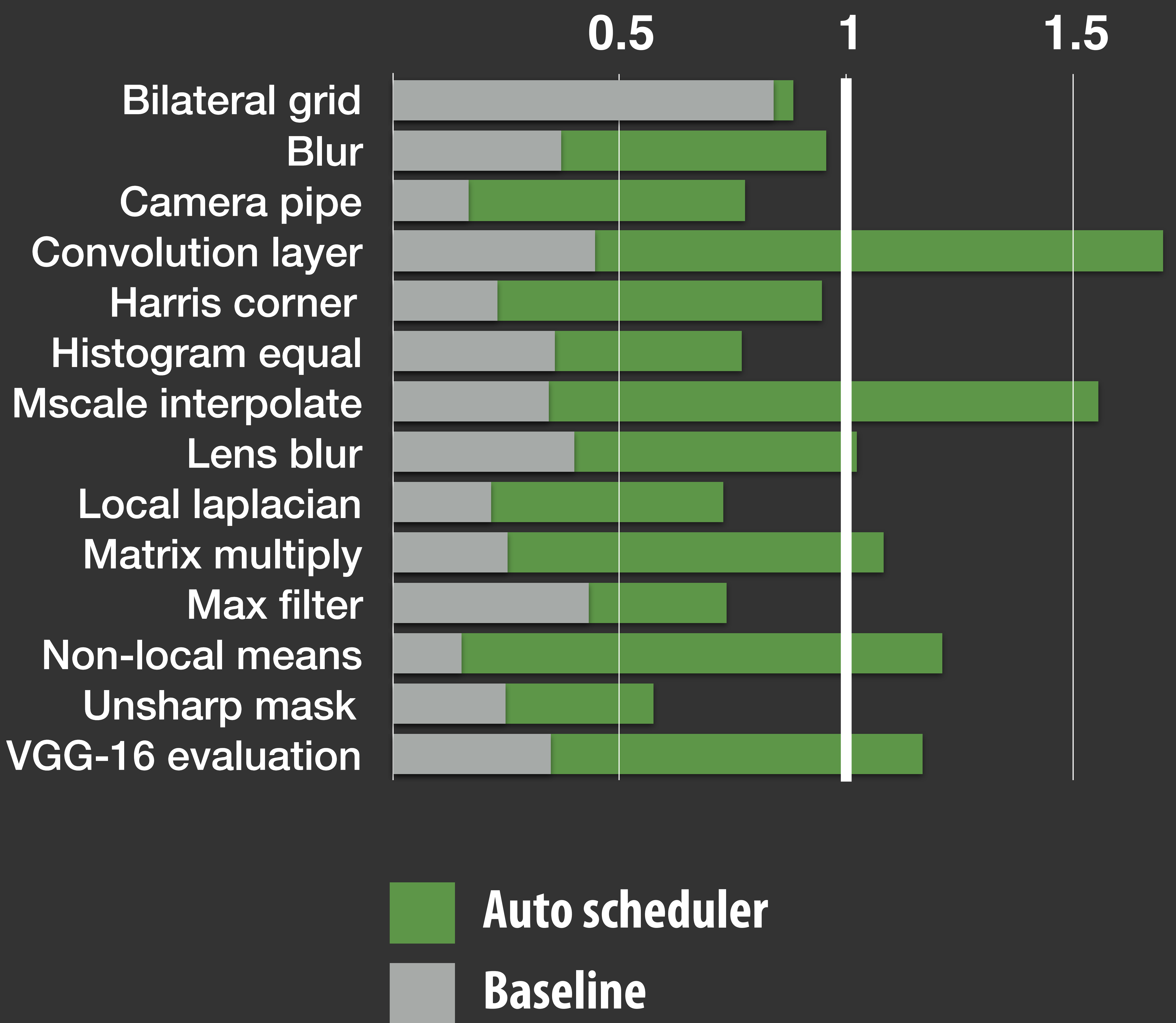
Autoscheduler generates schedules in seconds

Benchmark	Stages	Compile time (s)
Blur	3	<1
Unsharp mask	9	<1
Harris corner detection	13	<1
Camera RAW processing	30	<1
Non-local means denoising	13	<1
Max-brightness filter	9	<1
Multi-scale interpolation	52	2.6
Local-laplacian filter	103	3.9
Synthetic depth-of-field	74	55
Bilateral filter	8	<1
Histogram equalization	7	<1
VGG-16 deep network eval	64	6.9

Autoscheduler performs comparably to experts

Performance relative to schedules authored by experts

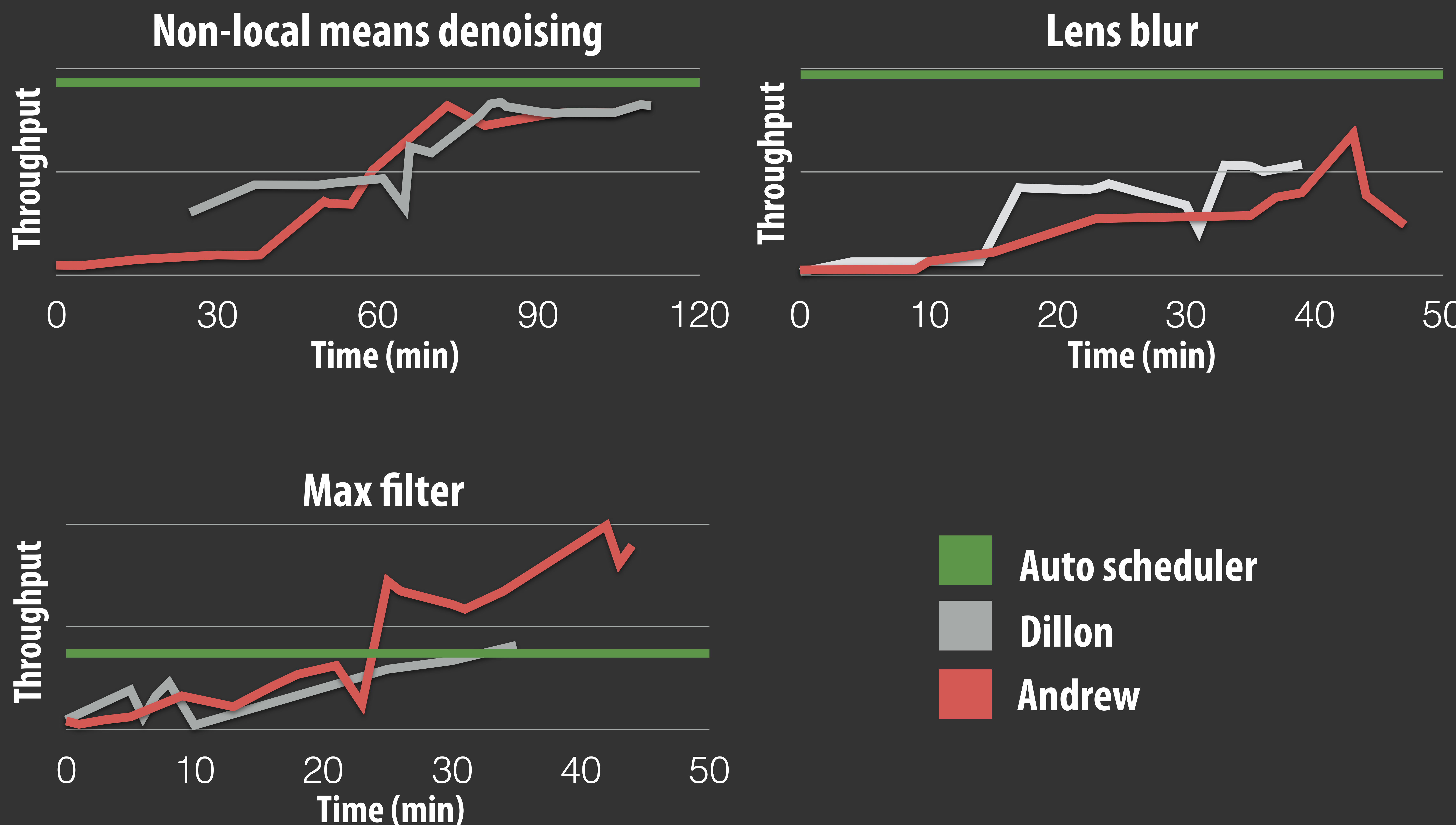
(6 core Xeon CPU)



On 8 of the 14 benchmarks performance within 10% of experts or better

Baseline schedules exploit multi-core/vector parallelism and pointwise inlining but no global locality optimizations

Autoscheduler saves time for experts



Impact / tech transfer

Auto scheduler now maintained by Google's Halide team

- If you write a Halide program, you can now schedule it with `.autoschedule()`
- Works quite well for CPU targets (x86/ARM)
- Works okay for GPU targets
- Will generate better schedulers in <1 sec than I would be able to create manually in a few days
- May not beat top developers at a major company, but gives them a strong head start

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