High-Performance Image Processing

Frédo Durand
most slides by Jonathan Ragan-Kelley
MIT CSAIL

4D lightfields: orders of magnitude from “good enough”

Current Lytro

10 Mrays

<1 Mpixels

5 secs

(on desktop PC)

Scale to 4k video

100 Mrays

8 Mpixels

1 min/*frame*

(on desktop PC)

[Ng 2005; Ng et al. 2006]
images by Ren Ng, Lytro

4D lightfields: orders of magnitude from “good enough”

Current Lytro

10 Mrays
<1 Mpixels
5 secs
(on desktop PC)

Scale to 4k video

100 Mrays
8 Mpixels
1 min/*frame*
(on desktop PC)

1 hour to process
1 second of video

[Ng 2005; Ng et al. 2006]
images by Ren Ng, Lytro

Rendering: orders of magnitude from “good enough”

images by Valve, Weta

Modern game: Team Fortress 2

2 Mpixels

0.5 Mpolys

10 ms/frame

CG movie: Tintin, Avatar

8 Mpixels

5 Gpolys

5 hrs/frame

Rendering: orders of magnitude from "good enough"

10 ms

5 hrs

6 orders of magnitude more computation

images by Valve, Weta

Modern game: Team Fortress 2

2 Mpixels

0.5 Mpolys

10 ms/frame

CG movie: Tintin, Avatar

8 Mpixels

5 Gpolys

5 hrs/frame

3D printing: orders of magnitude from “good enough”

1500 cm^3 shoe,
10 µm detail,
16 materials

2500^3 DPI
10^{12} voxels
25 terabytes

3D printing: orders of magnitude from “good enough”

1500 cm³ shoe,
10 µm detail,
16 materials

2500^3 DPI
10^{12} voxels
25 terabytes

10 shoes/hour = 4B voxels/sec

Pervasive sensing: orders of magnitude from "good enough"

Sensor + Read out

5 Mpixels

~1 mJ/frame

Eulerian Video Magnification [Wu et al. 2012]

Pervasive sensing: orders of magnitude from “good enough”

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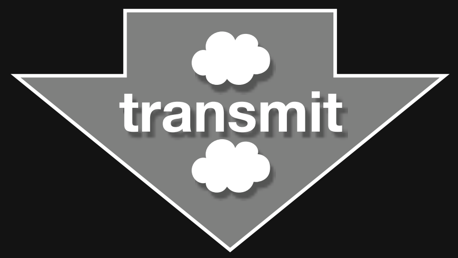


LTE radio

50 Mbit/sec

1 W

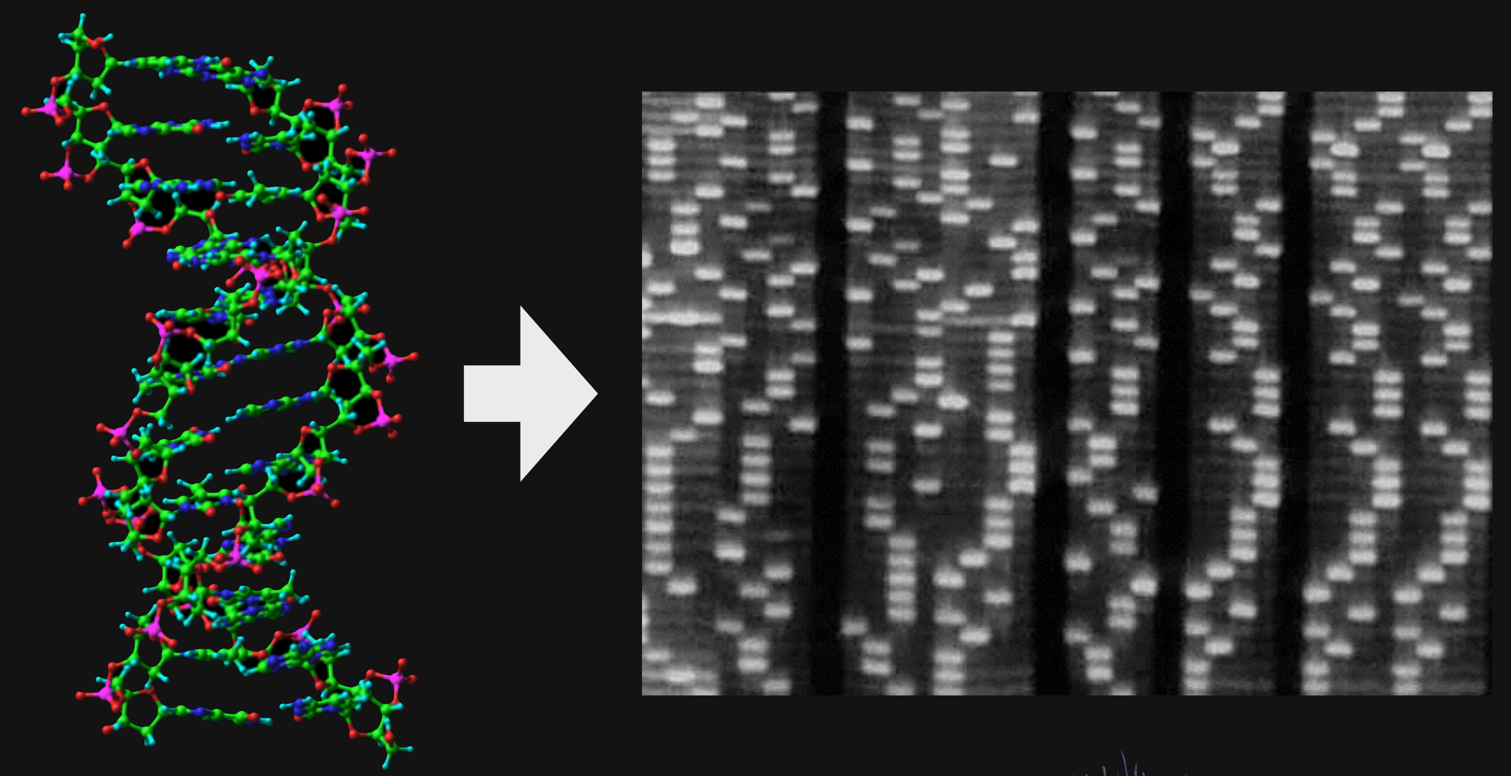
~1 J/frame

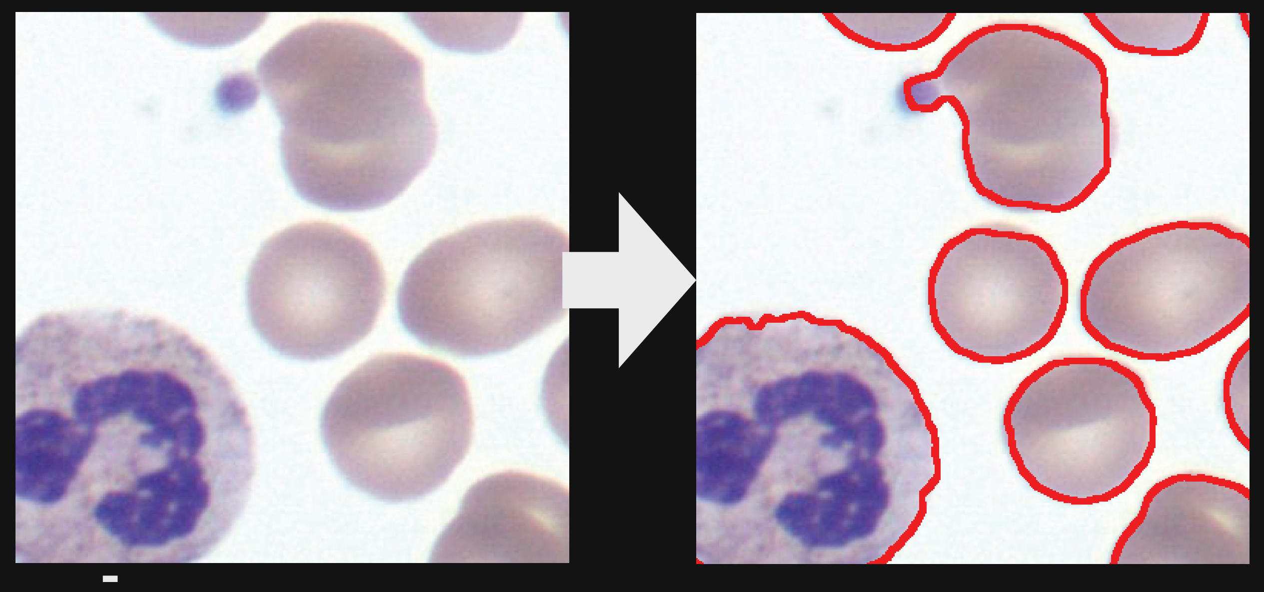
Eulerian Video Magnification [Wu et al. 2012]

transmission power costs 1,000x capture

High throughput imaging: orders of magnitude from “good enough”

most sensing is “imaging”





Your data-intensive problem here…

Making image processing faster

Faster algorithms

Faster Hardware

Parallelism

Memory behavior

Algorithmic acceleration (not today's topic though)

Sometimes exact, sometimes approximate

e.g. Fast box blur

Separable (exact)

Incremental (3 taps instead of 2*radius, exact)

(box(x+1)=box(x)+input(x-radius)+input(x+radius+1)

e.g. Bilateral Grid (approximate)

e.g. lookup tables (approximate)

See e.g. Andrew Adams' slides http://www.stanford.edu/class/cs448f/lectures/2.2/Fast%20Filtering.pdf

Algorithmic acceleration (not today's topic though)

e.g. Fast Gaussian blur

Separable (exact)

Recursive (approximate)

$$G(x+1) = aG(x) + bG(x-1) \ldots + a' I(x) + b' I(x-1)$$

Iterated Box (approximate)

FFT (exact up to wraparound)

See e.g. Andrew Adams' slides

http://www.stanford.edu/class/cs448f/lectures/2.2/Fast%20Filtering.pdf

Faster hardware

Faster CPU

More GHZ

More parallelism (multicore, SIMD vector-unit). But hard to program

Better memory bandwidth

Single Instruction Multiple Data SSE (typically 8 wide)

Graphics Hardware

Lots of parallelism

Can be annoying to program and debug (CUDA)

programming language

Can we better exploit hardware?

Parallelism

Good cache coherence

Requires to reorganize computation!

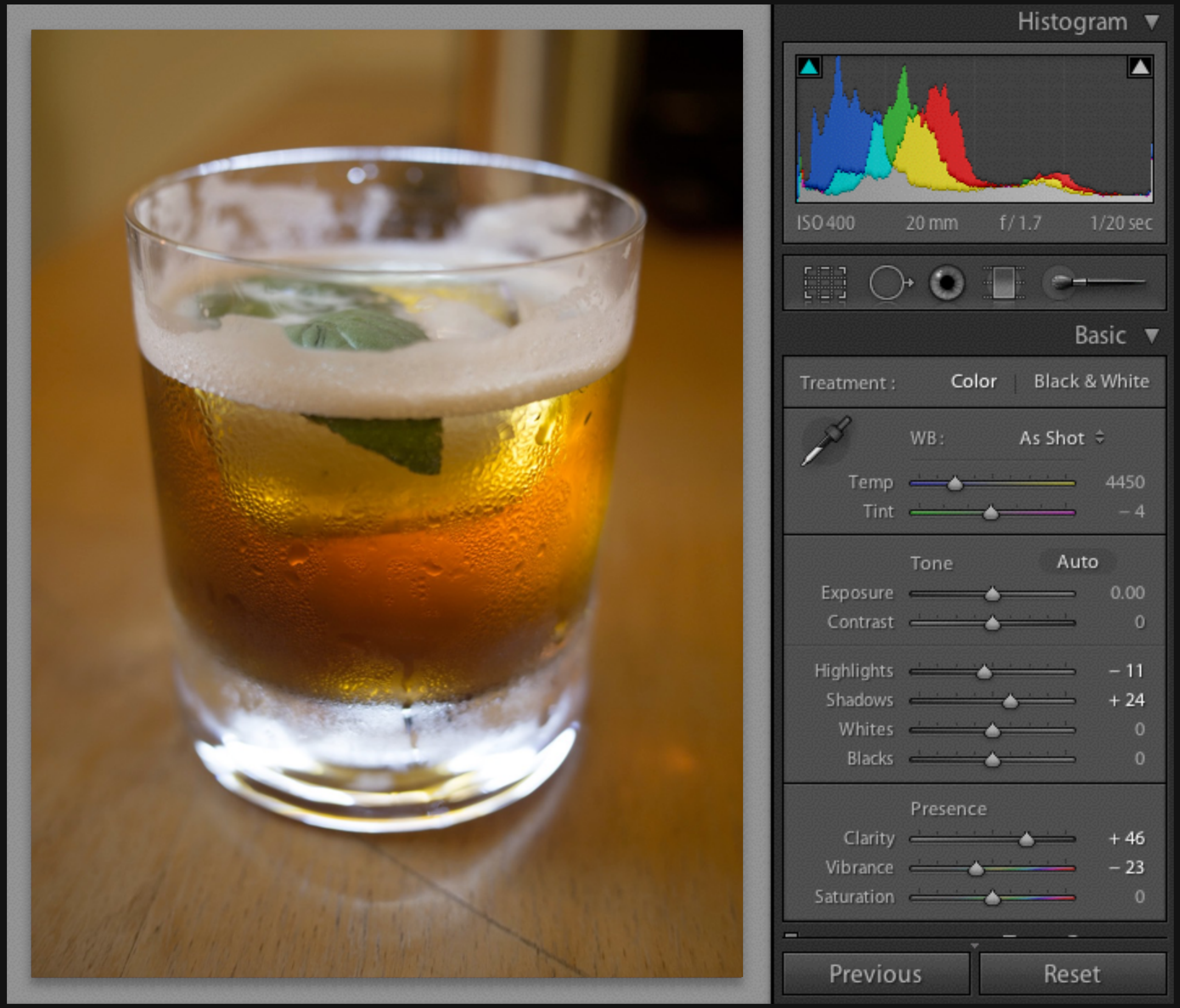
e.g. Local Laplacian Filtering

Reference: 300 lines C++

Adobe: 1500 lines

3 months of work

10x faster *(vs. reference)*



Spoiler: e.g. Local Laplacian Filtering

Reference: 300 lines C++

Adobe: 1500 lines

3 months of work

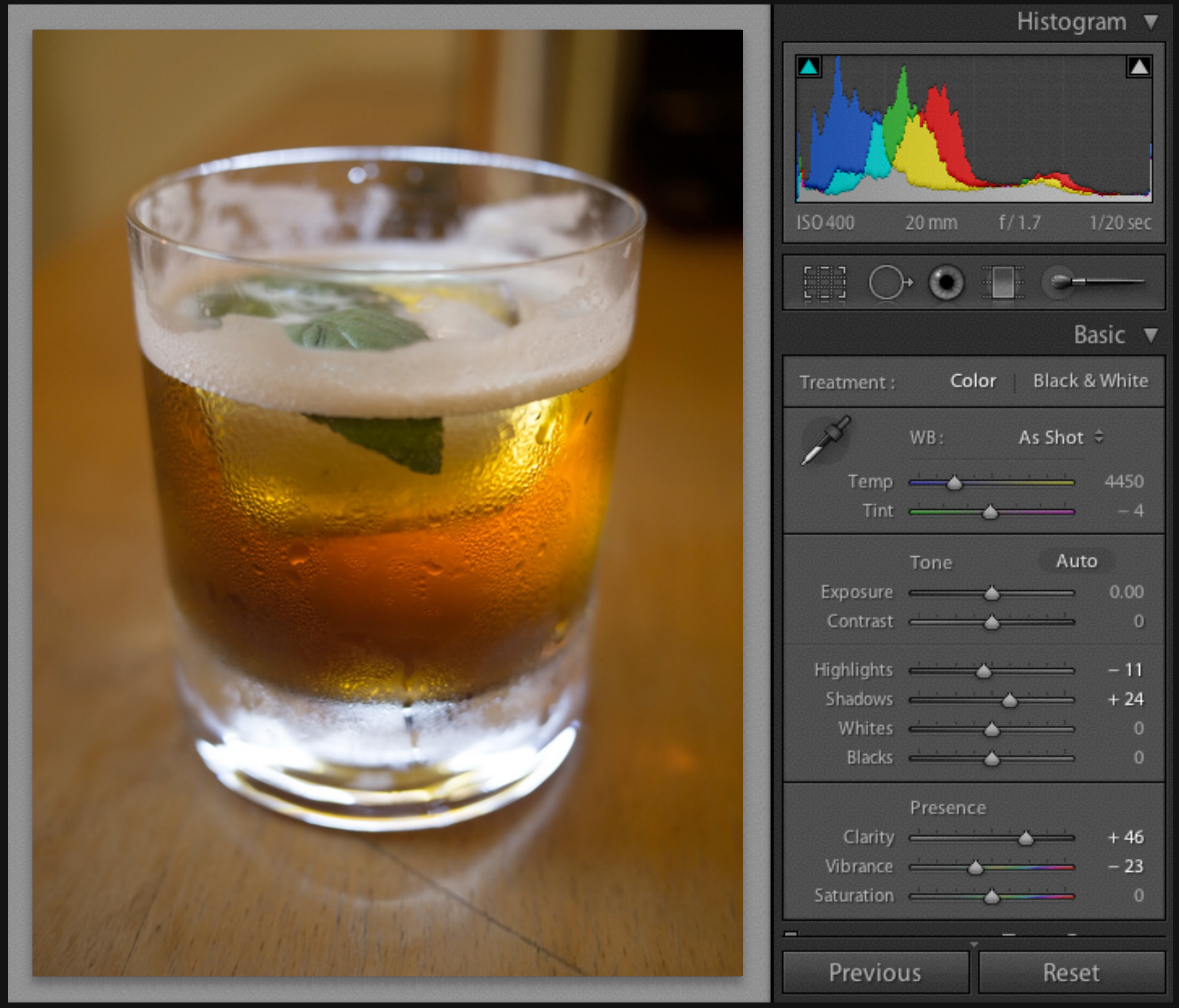
10x faster *(vs. reference)*

Parallelize (multicore)

Parallelize (SIMD vectorization)

Organized into tiles to maximize locality

Other tricks



Spoiler: Simpler, Faster, Scalable

Reference: 300 lines C++

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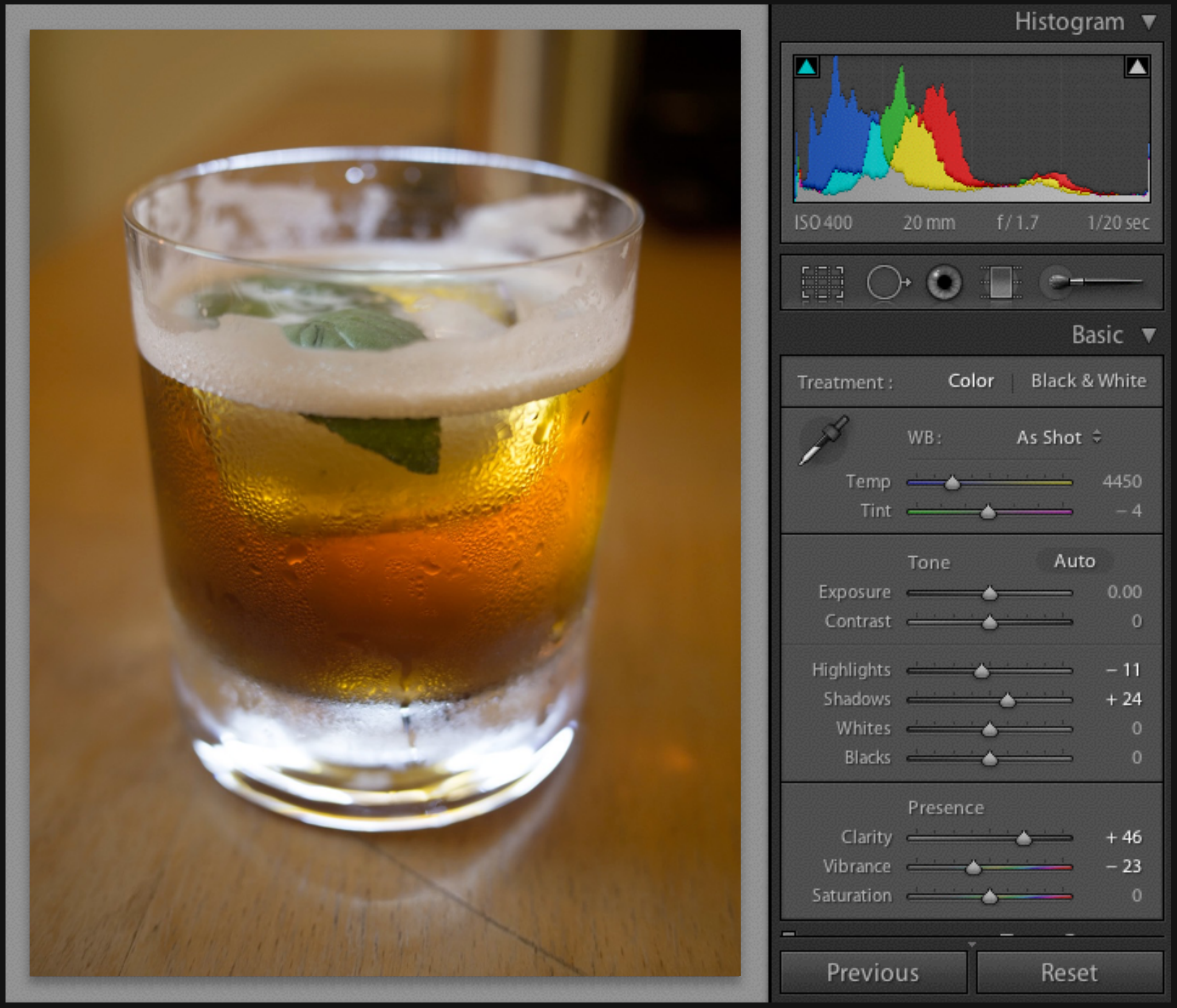
3 months of work
10x faster *(vs. reference)*

Halide: 60 lines
1 intern-day

20x faster (vs. reference)
2x faster (vs. Adobe)

GPU: 70x faster (vs. reference)



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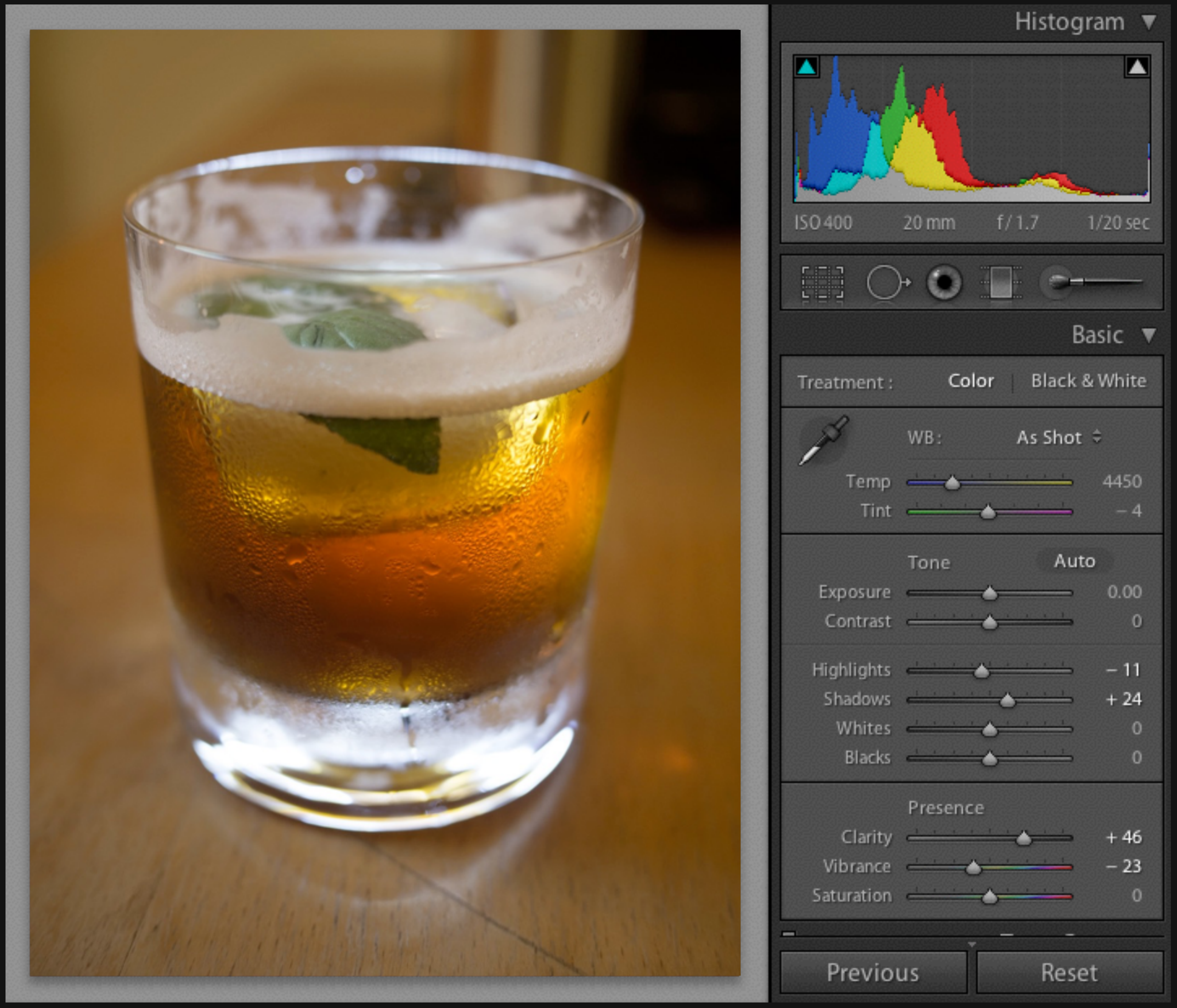


How can we get there?

How can we get there?

Parallelism
"Moore's law" growth will require exponentially more parallelism.

- frequency doesn't increase much
- pipeline parallelism has peaked

How can we get there?

Parallelism
"Moore's law" growth will require exponentially more parallelism.

Locality
Data should move as little as possible.

Communication dominates computation
in both energy and time

Operation (32-bit operands)	Energy/Op (28 nm)	*Cost* *(vs. ALU)*
ALU op		
Load from SRAM		
Move 10mm on-chip		
Send off-chip		
Send to DRAM		
Send over LTE		

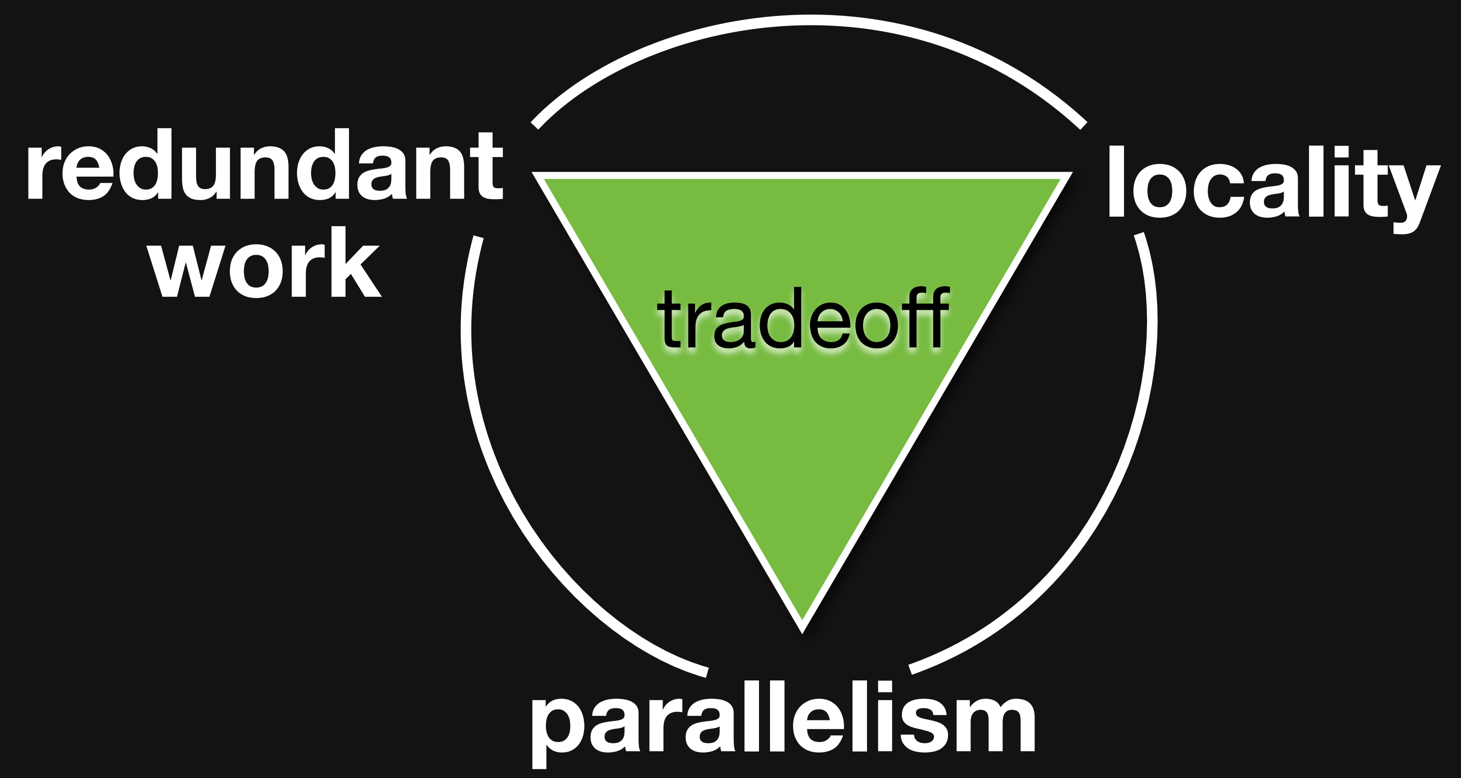
data from John Brunhaver, Bill Dally, Mark Horowitz

Communication dominates computation
in both energy and time

Operation (32-bit operands)	**Energy/Op** (28 nm)	***Cost*** *(vs. ALU)*
ALU op	1 pJ	-
Load from SRAM	1-5 pJ	*5x*
Move 10mm on-chip	32 pJ	*32x*
Send off-chip	500 pJ	*500x*
Send to DRAM	1 nJ	*1,000x*
Send over LTE	>10 μJ	*10,000,000x*

data from John Brunhaver, Bill Dally, Mark Horowitz

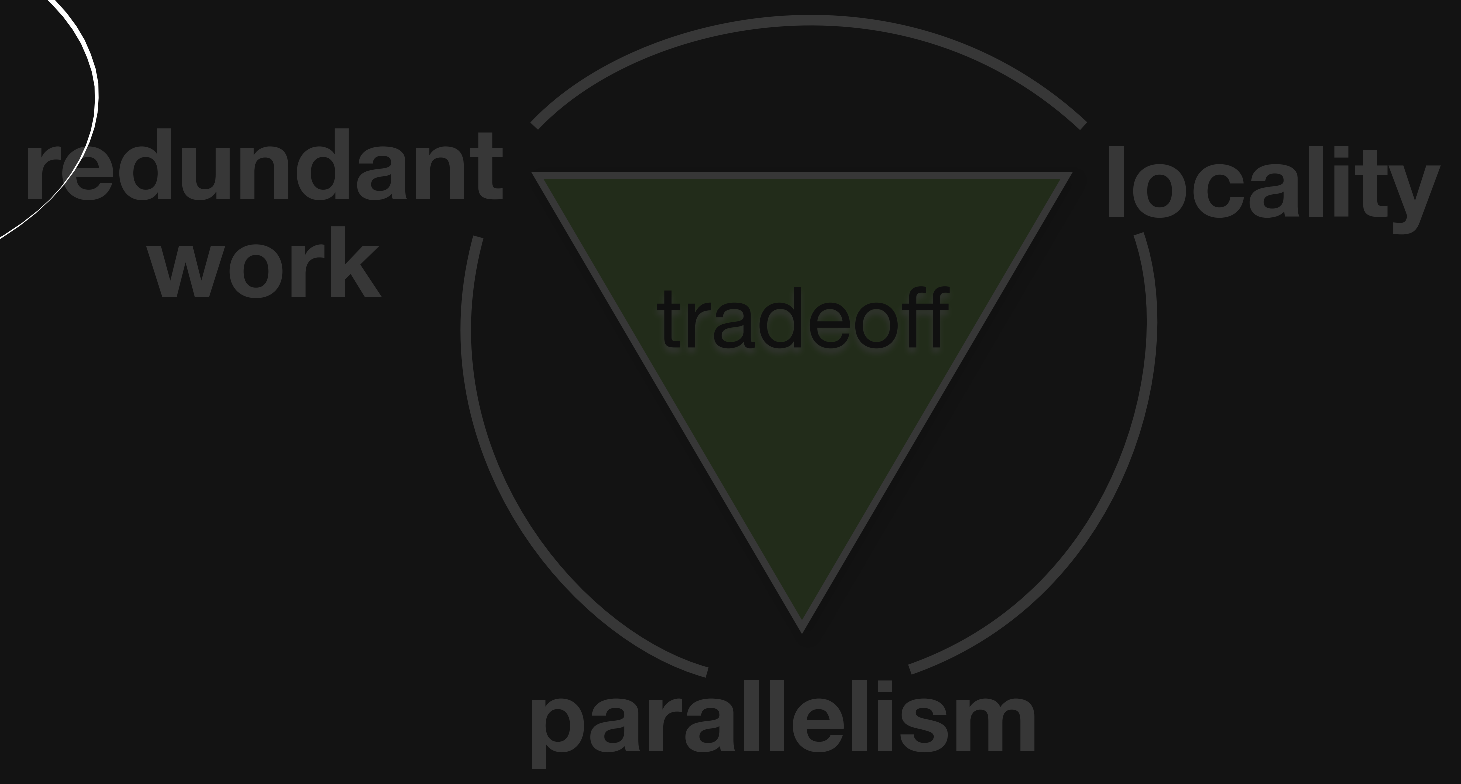
Message #1: Performance requires complex tradeoffs



Where does performance come from?

program → algorithm
→ organization of computation

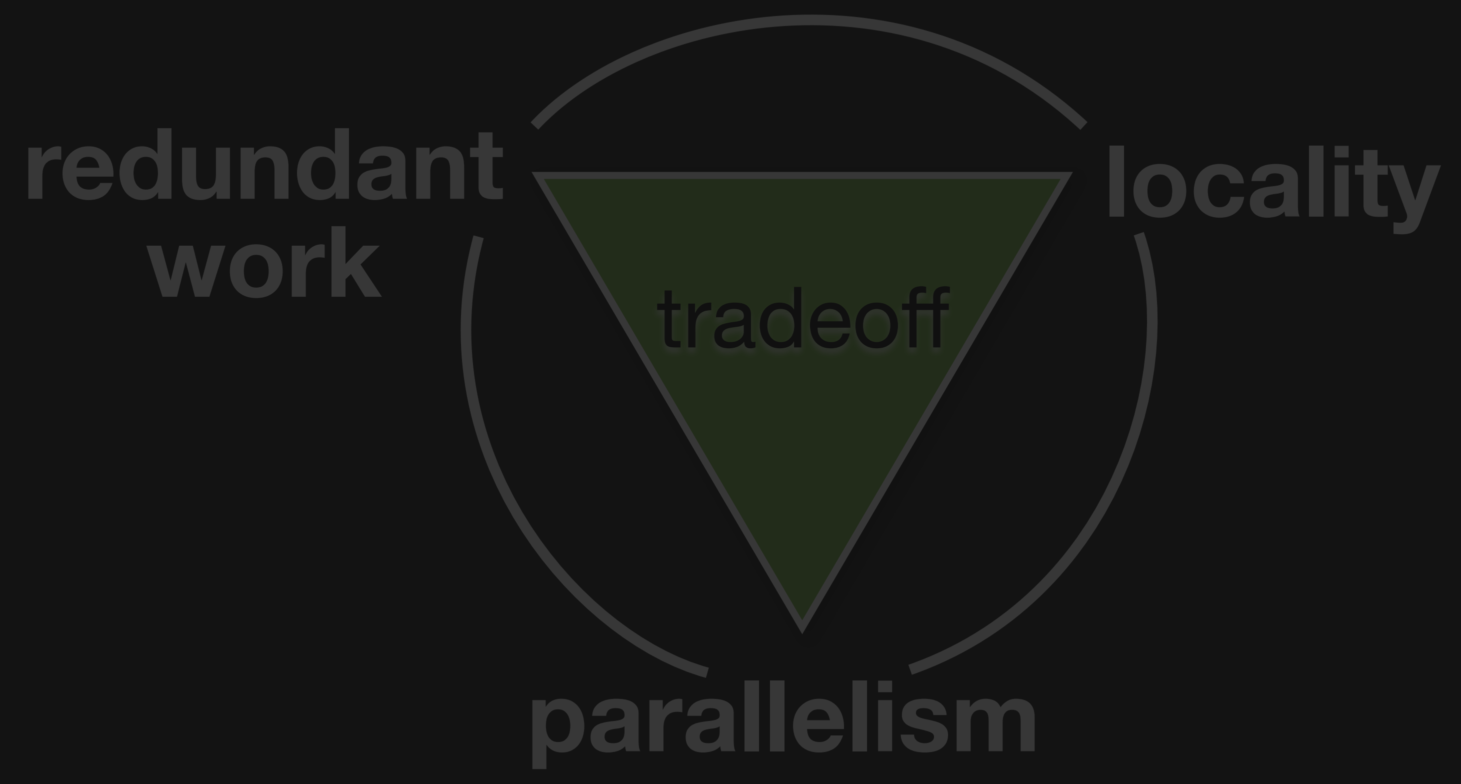
Hardware



Where does performance come from?

Program

Hardware

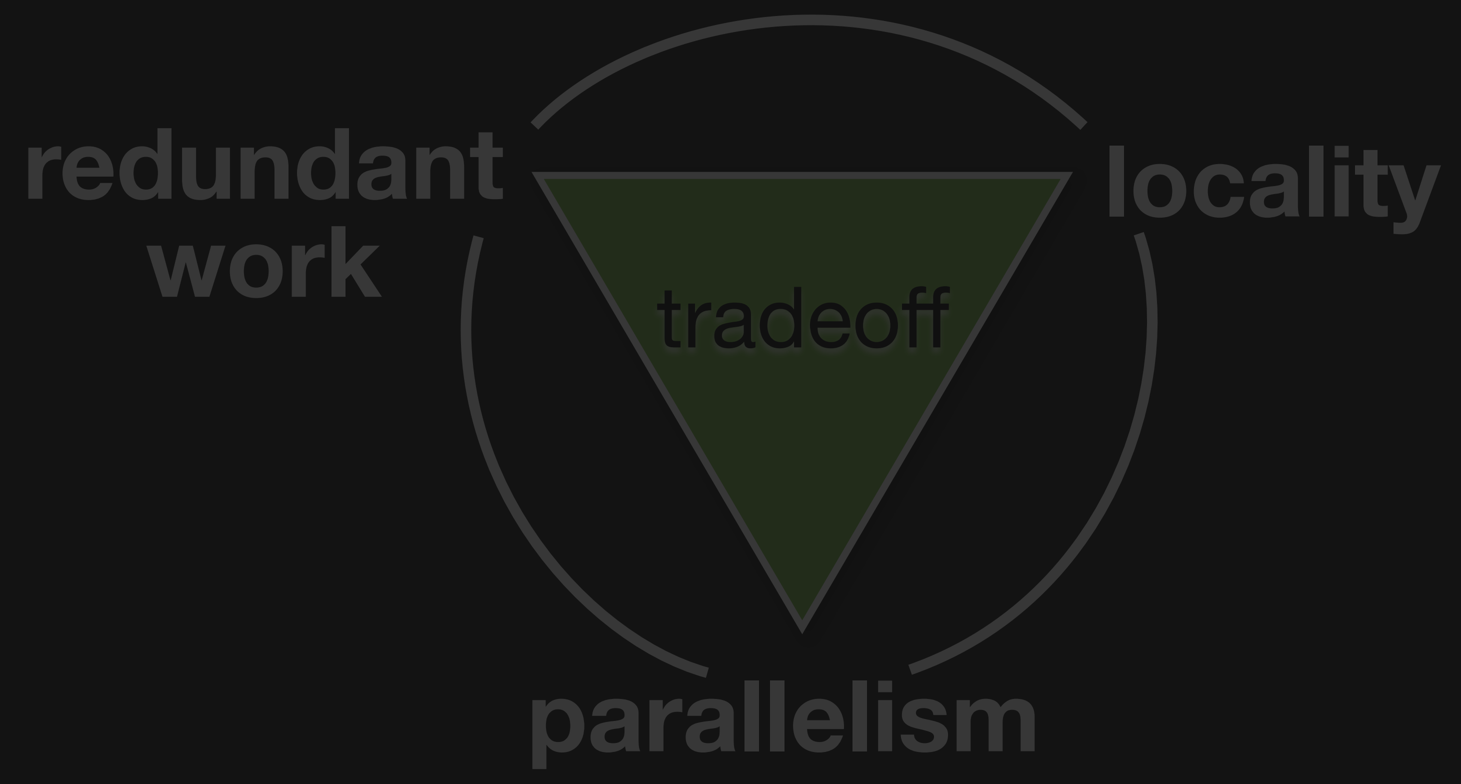


Message #2: organization of computation
is a first-class issue

Program:

Program

Hardware



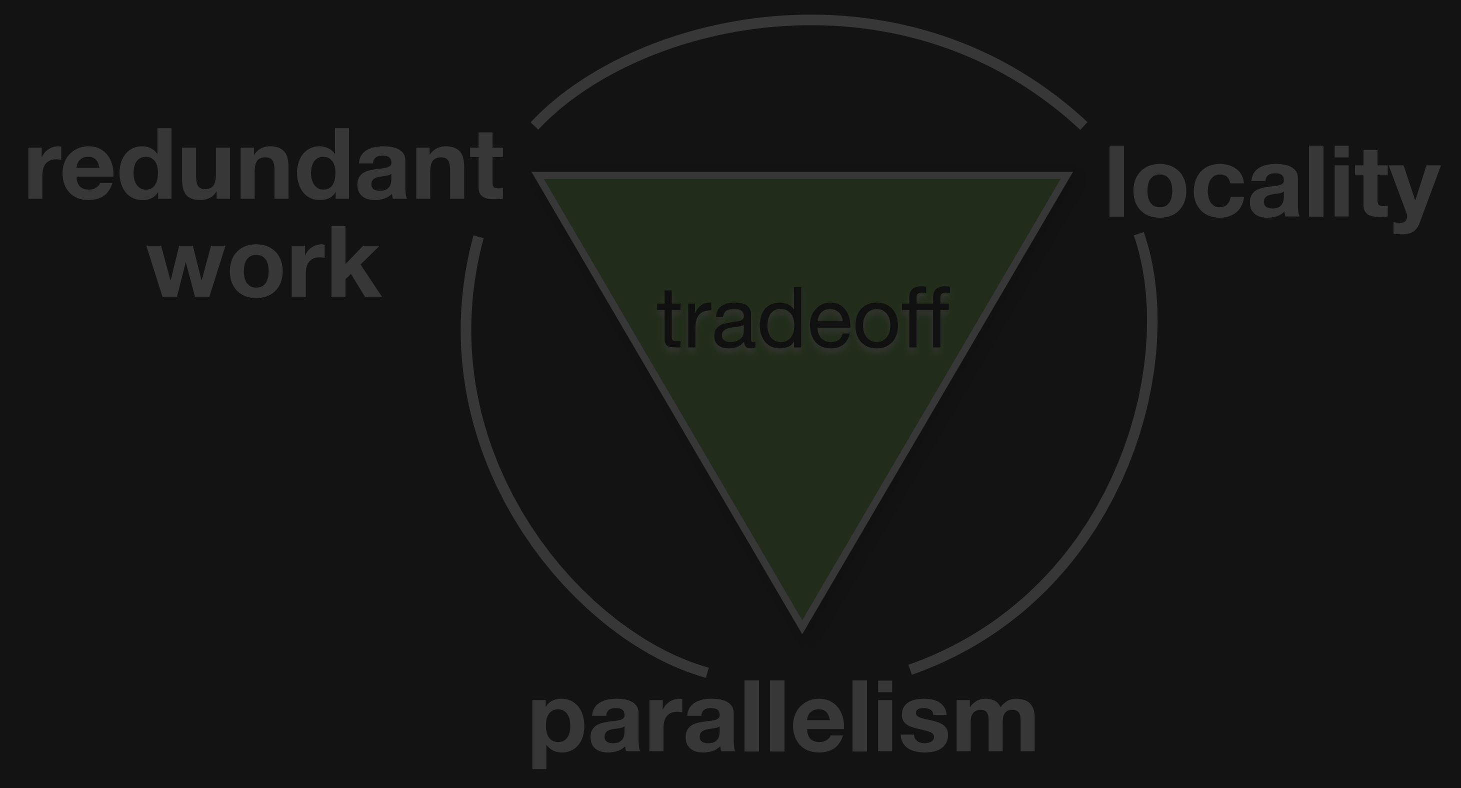
Message #2: organization of computation is a first-class issue

Program:

Algorithm

Organization of computation

Hardware



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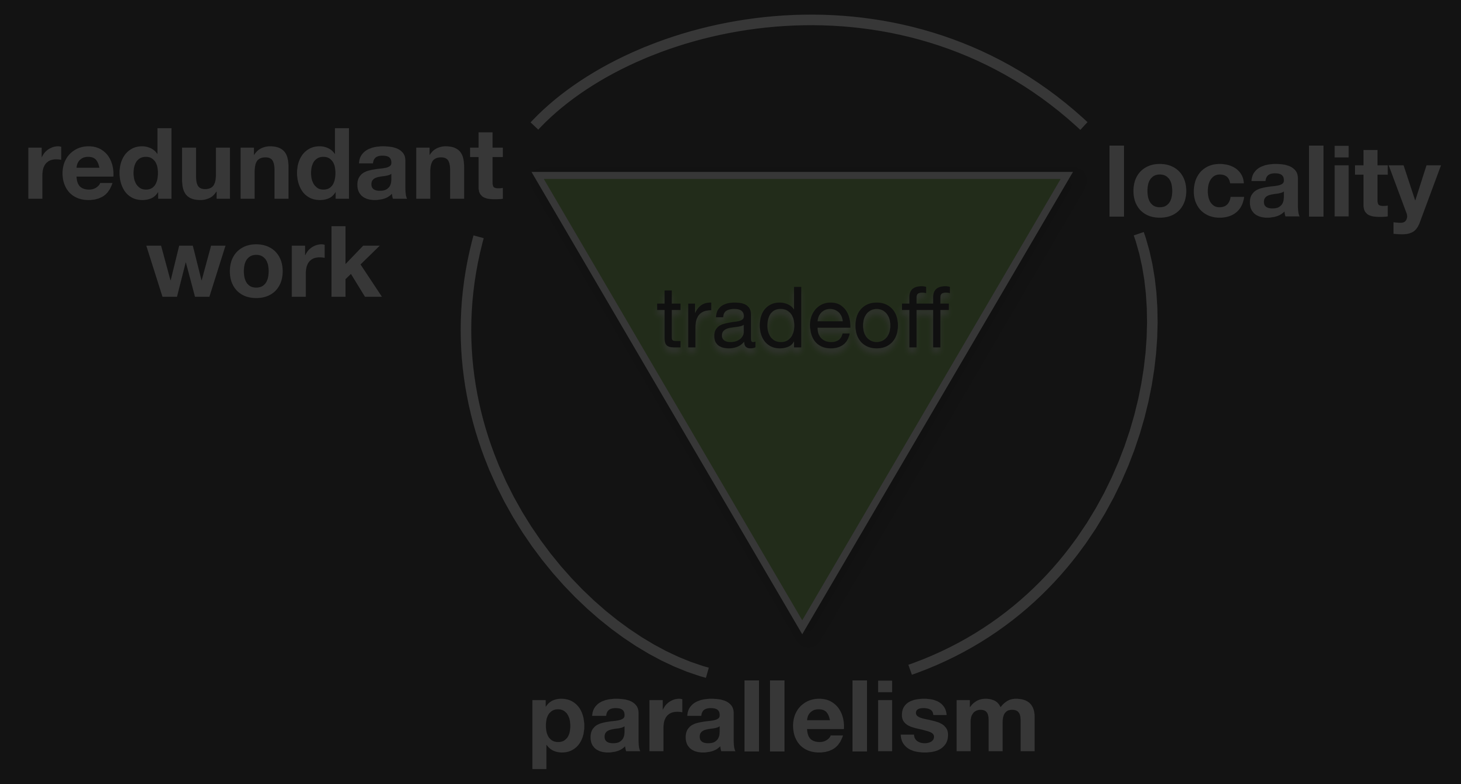
Program:

Algorithm

Organization of computation

Hardware



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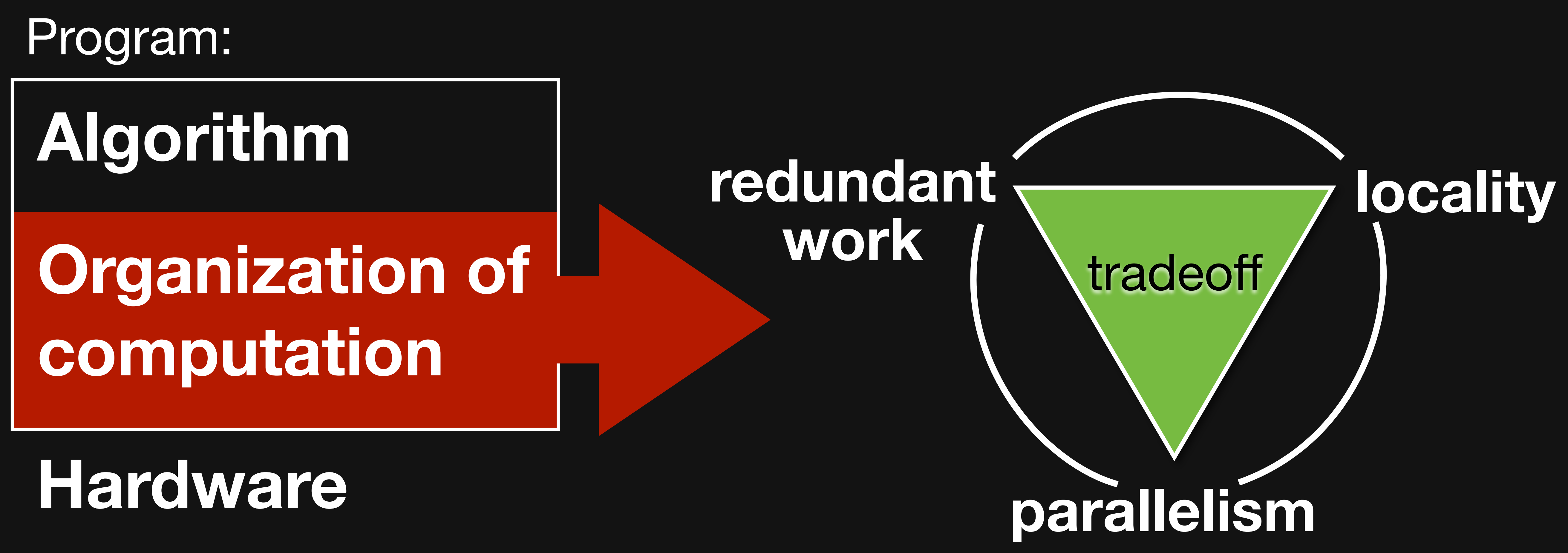


Halide

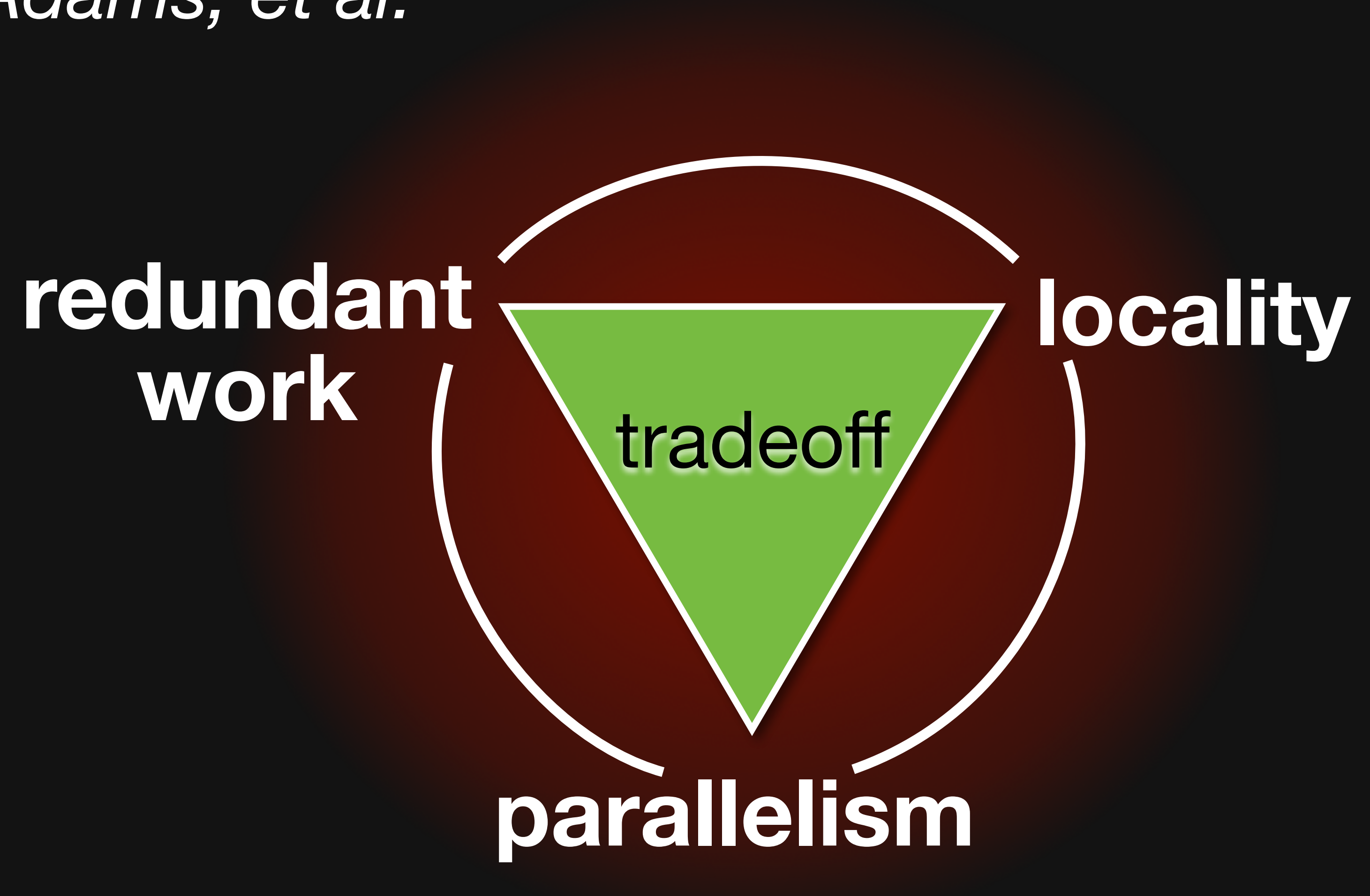
a language and compiler for image processing

[SIGGRAPH 2012, PLDI 2013]
Ragan-Kelley, Adams, et al.

Algorithm

Organization of computation

Hardware



Algorithm vs. Organization: 3x3 blur

```
void box_filter_3x3(const Image &in, Image &blury) {
  Image blurx(in.width(), in.height());  // allocate blurx array

  for (int x = 0; x < in.width(); x++)
    for (int y = 0; y < in.height(); y++)
      blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;

  for (int x = 0; x < in.width(); x++)
    for (int y = 0; y < in.height(); y++)
      blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
}
```

intermediate

final

Algorithm vs. Organization: 3x3 blur

```
void box_filter_3x3(const Image &in, Image &blury) {
  Image blurx(in.width(), in.height());  // allocate blurx array

  for (int x = 0; x < in.width(); x++)
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      blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;

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}
```

Algorithm vs. Organization: 3x3 blur

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  for (int y = 0; y < in.height(); y++)
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      blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;

  for (int y = 0; y < in.height(); y++)
    for (int x = 0; x < in.width(); x++)
      blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
}
```

15x faster

because better memory coherence

Algorithm vs. Organization: 3x3 blur

```
void box_filter_3x3(const Image &in, Image &blury) {
  Image blurx(in.width(), in.height());  // allocate blurx array

  for (int y = 0; y < in.height(); y++)
    for (int x = 0; x < in.width(); x++)
      blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;

  for (int y = 0; y < in.height(); y++)
    for (int x = 0; x < in.width(); x++)
      blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
}
```

Same algorithm, different organization

One of them is 15x faster

Why swapping loops make things faster/slower

In general

Reorganize computationto maximize parallelism & locality

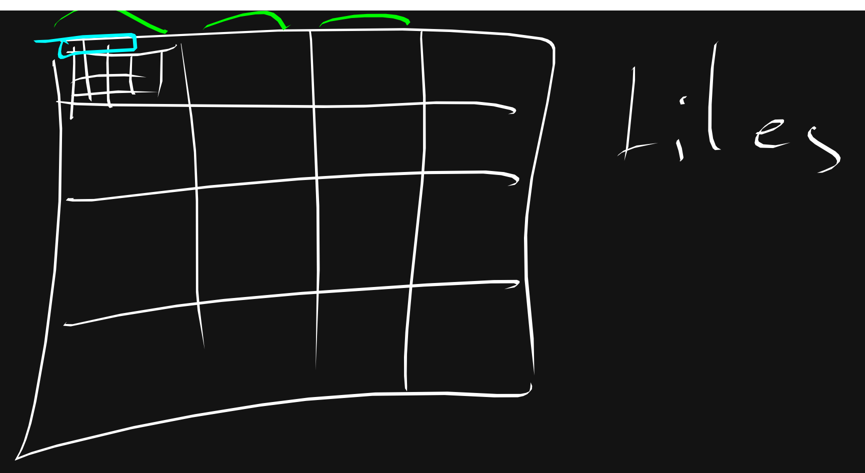
e.g. compute in tiles, merge pipeline stages

e.g. compute blur_x and blur_y for a full tile, compute tiles in parallel, leverage SIMD vector units

Hand-optimized C++

9.9 → 0.9 ms/megapixel

```
void box_filter_3x3(const Image &in, Image &blury) {
  __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 blurx[(256/8)*(32+2)]; // allocate tile blurx array
    for (int xTile = 0; xTile < in.width(); xTile += 256) {
      __m128i *blurxPtr = blurx;
      for (int y = -1; y < 32+1; y++) {
        const uint16_t *inPtr = &(in[yTile+y][xTile]);
        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(blurxPtr++, avg);
         inPtr += 8;
      }}
      blurxPtr = blurx;
      for (int y = 0; y < 32; y++) {
        __m128i *outPtr = (__m128i *)(&(blury[yTile+y][xTile]));
        for (int x = 0; x < 256; x += 8) {
          a = _mm_load_si128(blurxPtr+(2*256)/8);
          b = _mm_load_si128(blurxPtr+256/8);
          c = _mm_load_si128(blurxPtr++);
          sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
          avg = _mm_mulhi_epi16(sum, one_third);
          _mm_store_si128(outPtr++, avg);
}}}}}
```



Tiled, fused

Vectorized

Multithreaded

Redundant computation

Near roof-line optimum

Hand-optimized C++

9.9 → 0.9 ms/megapixel

```
void box_filter_3x3(const Image &in, Image &blury) {
  __m128i one_third = _mm_set1_epi16(21846);
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    __m128i blurx[(256/8)*(32+2)]; // allocate tile blurx array
    for (int xTile = 0; xTile < in.width(); xTile += 256) {
      __m128i *blurxPtr = blurx;
      for (int y = -1; y < 32+1; y++) {
        const uint16_t *inPtr = &(in[yTile+y][xTile]);
        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(blurxPtr++, avg);
         inPtr += 8;
      }}
      blurxPtr = blurx;
      for (int y = 0; y < 32; y++) {
        __m128i *outPtr = (__m128i *)(&(blury[yTile+y][xTile]));
        for (int x = 0; x < 256; x += 8) {
          a = _mm_load_si128(blurxPtr+(2*256)/8);
          b = _mm_load_si128(blurxPtr+256/8);
          c = _mm_load_si128(blurxPtr++);
          sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
          avg = _mm_mulhi_epi16(sum, one_third);
          _mm_store_si128(outPtr++, avg);
}}}}}
```

11x faster
(quad core x86)

Tiled, fused

Vectorized

Multithreaded

Redundant computation

Near roof-line optimum

(Re)organizing computation is hard

Optimizing parallelism, locality requires
transforming program & data structure.

What transformations are *legal*?

What transformations are *beneficial?*

(Re)organizing computation is hard

Optimizing parallelism, locality requires
transforming program & data structure.

What transformations are *legal?*

What transformations are *beneficial?*

libraries don't solve this:
BLAS, IPP, MKL, OpenCV, MATLAB
optimized kernels compose into inefficient pipelines (no fusion)

Halide's answer: *decouple* algorithm from schedule

organization

Algorithm: formula for desired value at pixel

no notion of loop

Schedule: organization of computation

when computed where stored

within a pipeline stage

across pipeline stages

co-language

Halide's answer: *decouple* algorithm from schedule

Algorithm: ***what*** is computed
Schedule: ***where*** and ***when*** it's computed

Easy for programmers to build pipelines

Easy to specify & explore optimizations
manual or automatic search

Easy for the compiler to generate fast code

Halide *algorithm*:

```
blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
```

no loop, it's implicit

Halide *algorithm*:

```
blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
```

Halide *schedule*:

```
blury.tile(x, y, xi, yi, 256, 32).vectorize(xi, 8).parallel(y);
blurx.compute_at(blury, x).store_at(blury, x).vectorize(x, 8);
```

tile index

within tile

size of tile

DSL

language

SIMD

multicore

most important

always start with output

Prior work*

*a tiny sample. Thousands have come before us.

Streaming languages
Ptolemy [Buck et al. 1993]
StreamIt [Thies et al. 2002]
Brook [Buck et al. 2004]

Loop optimization
Systolic arrays [Gross & Lam 1984]
Polyhedral model [Ancourt & Irigoin 1991, Amarasinghe & Lam 1993]

Parallel work scheduling
Cilk [Blumhofe et al. 1995]
NESL [Blelloch et al. 1993]

Region-based languages
ZPL [Chamberlain et al. 1998]
Chapel [Callahan et al. 2004]

Stencil optimization & DSLs
[Frigo & Strumpen 2005]
[Krishnamoorthy et al. 2007]
[Kamil et al. 2010]

Mapping-based languages & DSLs
SPL/SPIRAL [Püschel et al. 2005]
Sequoia [Fatahalian et al. 2006]

Shading languages
RSL [Hanrahan & Lawson 1990]
Cg, HLSL [Mark et al. 2003; Blythe 2006]

Image processing systems
[Shantzis 1994], [Levoy 1994]
PixelBender, CoreImage

Halide

0.9 ms/megapixel

```
Func box_filter_3x3(Func in) {
  Func blurx, blury;
  Var x, y, xi, yi;

  // The algorithm - no storage, order
  blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
  blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;

  // The schedule - defines order, locality; implies storage
  blury.tile(x, y, xi, yi, 256, 32)
       .vectorize(xi, 8).parallel(y);
  blurx.compute_at(blury, x).store_at(blury, x).vectorize(x, 8);

  return blury;
}
```

C++

0.9 ms/megapixel

```
void box_filter_3x3(const Image &in, Image &blury) {
  __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 blurx[(256/8)*(32+2)]; // allocate tile blurx array
    for (int xTile = 0; xTile < in.width(); xTile += 256) {
      __m128i *blurxPtr = blurx;
      for (int y = -1; y < 32+1; y++) {
        const uint16_t *inPtr = &(in[yTile+y][xTile]);
        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(blurxPtr++, avg);
         inPtr += 8;
      }}
      blurxPtr = blurx;
      for (int y = 0; y < 32; y++) {
        __m128i *outPtr = (__m128i *)(&(blury[yTile+y][xTile]));
        for (int x = 0; x < 256; x += 8) {
          a = _mm_load_si128(blurxPtr+(2*256)/8);
          b = _mm_load_si128(blurxPtr+256/8);
          c = _mm_load_si128(blurxPtr++);
          sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
          avg = _mm_mulhi_epi16(sum, one_third);
          _mm_store_si128(outPtr++, avg);
}}}}}
```

How can we determine *good* schedules?

Explicit programmer control
The compiler does *exactly what you say*.
Schedules cannot influence correctness.
Exploration is fast and easy.

Stochastic search *(autotuning)*
Pick your favorite high-dimensional search.
(We used Petabricks' genetic algorithm tuner *[Ansel et al. 2009]*)

The Halide Language

Basic Halide program (default schedule)

```
Image<float> input = load<float>("images/rgb.png");

Var x, y;
Func blur_x;
Func blur_y;


blur_x(x,y) = (input(x,y)+input(x+1,y)+input(x+2,y))/3.0;
blur_y(x,y) = (blur_x(x,y)+blur_x(x,y+1)+blur_x(x,y+2))/3.0;


Image<float> output = blur_y.realize(input.width()-2,
input.height()-2);
```

Halide is an embedded language

build C++ data structure that represents a Halide program

```
Image<float> input = load<float>("images/rgb.png");

Var x, y;
Func blur_x;
Func blur_y;

blur_x(x,y) = (input(x,y)+input(x+1,y)+input(x+2,y))/3.0;
blur_y(x,y) = (blur_x(x,y)+blur_x(x,y+1)+blur_x(x,y+2))/3.0;

Image<float> output = blur_y.realize(input.width()-2,
input.height()-2);
```

C++ type

C++ type that represents Halide functions

overloaded operators

call Halide compiler + LLVM

Metaprogramming

Create C++ objects that describe a Halide program

Essentially algebraic trees (Abstract Syntax Tree, AST)

Metaprogramming

```
Image<float> input = load<float>("images/rgb.png");
Var x, y;
Func blur_x;
Func blur_y;
blur_x(x,y) = (input(x,y)+input(x+1,y)+input(x+2,y))/3.0;
blur_y(x,y) = (blur_x(x,y)+blur_x(x,y+1)+blur_x(x,y+2))/3.0;
```

Metaprogramming

Create C++ objects that describe a Halide program

Essentially algebraic trees (Abstract Syntax Tree, AST)

Once the representation is constructed, call .realize() to compile and execute

This calls the C++ Halide compiler, creates binary, executes it

Metaprogramming

Makes it easy to embed in an existing language and codebase

Avoids the need to parse

Syntax: Main types/keywords

functional language

Func : pure functions over an integer domain

Var : pure abstract variables for domain of Funcs

Expr: algebraic expressions of Funcs and Var
including standard operators and functions (+,-,&, /, **, sqrt, sin, cos...)

Image: arrays used as inputs and outputs

both Halide constructs & under the hood C++ classes

Basic Halide program (default schedule)

```
Image<float> input = load<float>("images/rgb.png");

Var x, y;
Func blur_x;
Func blur_y;


blur_x(x,y) = (input(x,y)+input(x+1,y)+input(x+2,y))/3.0;
blur_y(x,y) = (blur_x(x,y)+blur_x(x,y+1)+blur_x(x,y+2))/3.0;


Image<float> output = blur_y.realize(input.width()-2,
input.height()-2);
```

Loops are implicit