Dynamic Scheduling in Halide

cache rules everything around me

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Outline

Halide Review

- Function Definitions
- Function Scheduling

Dynamic Scheduling

- Problem: Dynamic Vector Fields
- Solution: Cache Computed Values

Evaluation

Image Processing is Functional Programming

```
blur_y(x,y) =
     (input(x, y-1) +
      input(x, y  ) +
      input(x, y+1))/3;
```

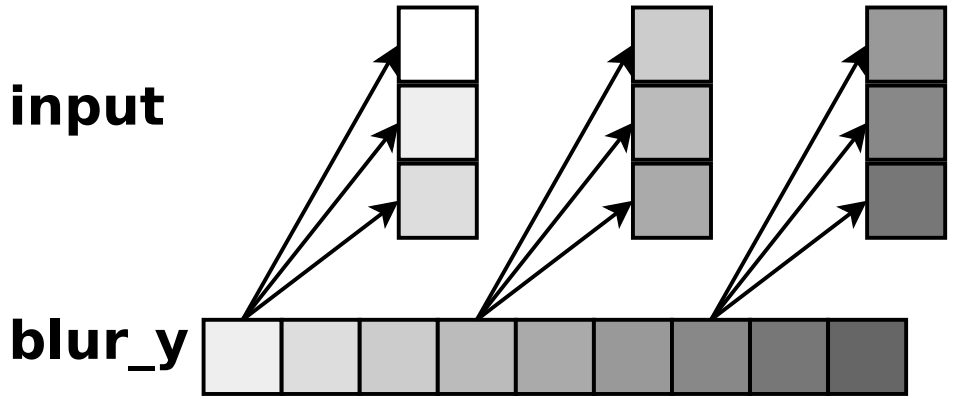
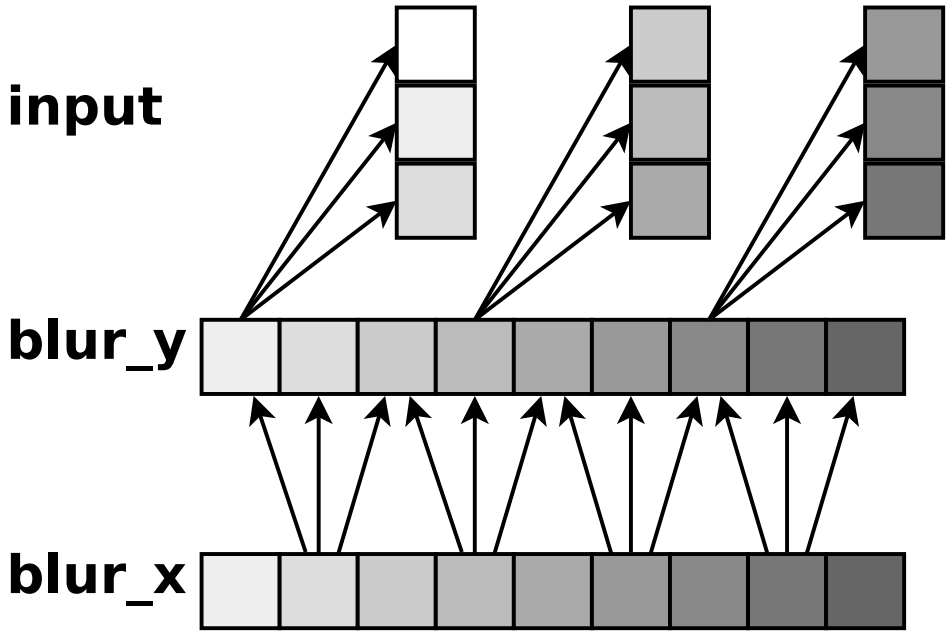


Image Processing is Functional Programming

```
blur_y(x,y) =
     (input(x, y-1) +
      input(x, y  ) +
      input(x, y+1))/3;

blur_x(x,y) =
     (blur_y(x-1, y) +
      blur_y(x,   y) +
      blur_y(x+1, y))/3;
```



...embedded in C++

```
void main(int argc, char **argv)
    Image<float> input = load(argv[1]);
    Image<float> output(input.width(), input.height());
    Func blur_y, blur_x;
    Var x,y;
    blur_y(x,y) = (input(x, y-1) + ...)/3;
    blur_x(x,y) = (blur_y(x-1, y) + ...)/3;

    blur_x.realize(output); // JITs and runs the blur
    save(output, "output.png");
}
```

...embedded in C++

```
class Expr { ...  };
class Func {
    operator()(Expr x, Expr y, Expr z, ...);
    ...
};
void main(int argc, char **argv)
    Image<float> input = load(argv[1]);
    Image<float> output(input.width(), input.height());
    Func blur_y, blur_x;
    Var x,y;
    blur_y(x,y) = (input(x, y-1) + ...)/3;
    blur_x(x,y) = (blur_y(x-1, y) + ...)/3;

    blur_x.realize(output); // JITs and runs the blur
    save(output, "output.png");
}
```

Functions are Automatically "Scheduled"

```
blur_y(x,y) =
  (input(x, y-1) +
   input(x, y,   c) +
   input(x, y+1))/3;

blur_x(x,y) =
  (blur_y(x-1, y) +
   blur_y(x,   y) +
   blur_y(x+1, y))/3;
```

```
float blur_y[HEIGHT][WIDTH];
for (row = 0 to HEIGHT) {
  for (col = 0 to WIDTH) {
    blur_y[row][col] = ...;
  }
}
float blur_x[HEIGHT][WIDTH];
for (row = 0 to HEIGHT) {
  for (col = 0 to WIDTH) {
    blur_x[row][col] = ...;
  }
}
```

Functions are Automatically "Scheduled"

```
blur_y(x,y) =
  (input(x, y-1) +
   input(x, y,   c) +
   input(x, y+1))/3;

blur_x(x,y) =
  (blur_y(x-1, y) +
   blur_y(x,   y) +
   blur_y(x+1, y))/3;
```

```
float blur_y[HEIGHT][WIDTH];
for (row = 0 to HEIGHT) {
  for (col = 0 to WIDTH) {
    blur_y[row][col] = ...;
  }
}
float blur_x[HEIGHT][WIDTH];
for (row = 0 to HEIGHT) {
  for (col = 0 to WIDTH) {
    blur_x[row][col] = ...;
  }
}
```

- Bad locality: Traversing the whole image twice
- Bad paralellism: One thread per row/column/pixel??

Function Schedules Can Be Configured

```
blur_x.tile(x, y, x2, y2, 8, 8).parallel(x, y);
blur_y.store_at(blur_x, x).compute_at(blur_x, y2);
```

Function Schedules Can Be Configured

```
blur_x.tile(x, y, x2, y2, 8, 8).parallel(x, y);
blur_y.store_at(blur_x, x).compute_at(blur_x, y2);
```

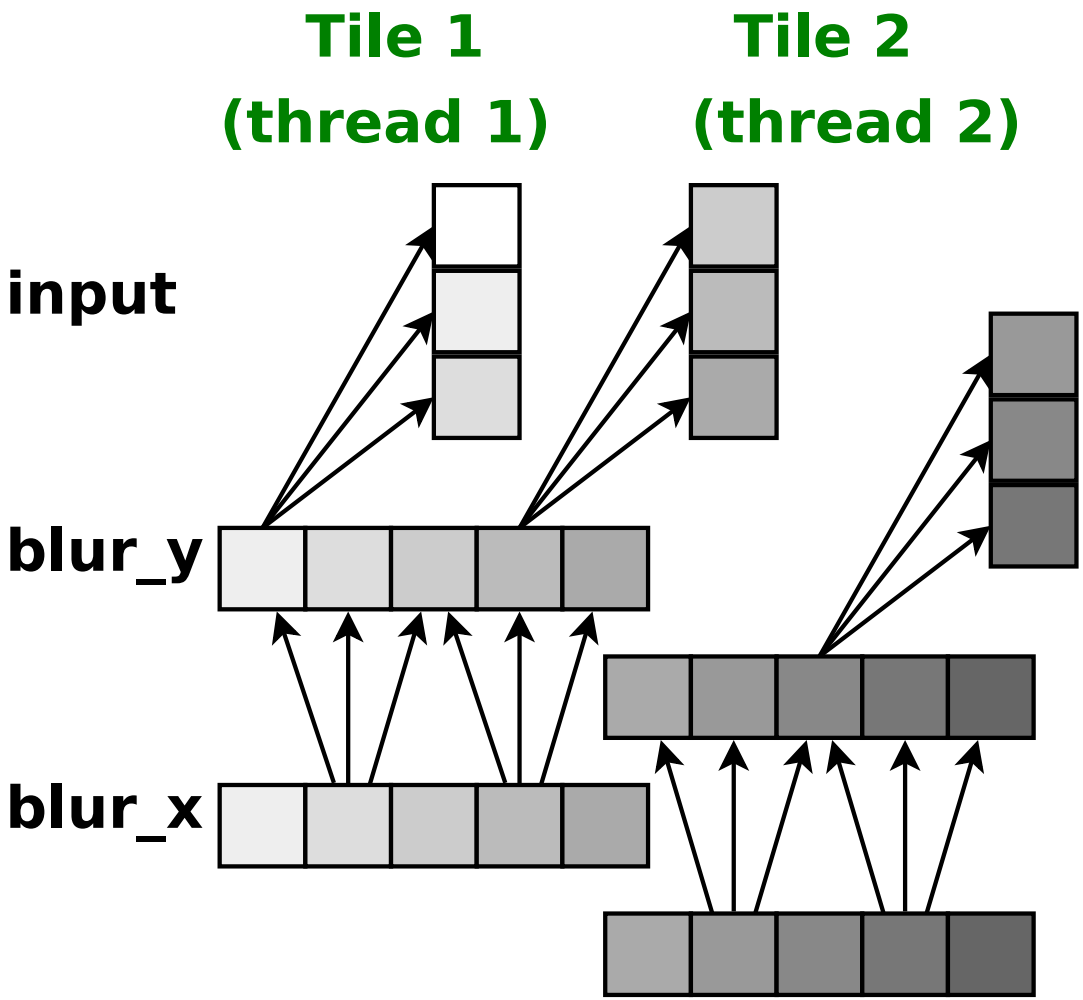
```
float blur_x[HEIGHT][WIDTH];
PARALLEL for (row = 0 to 8) {
  PARALLEL for (col = 0 to 8) {
    float blur_y[HEIGHT/8][WIDTH/8];
    for (row2 = 0 to WIDTH/8) {
      for (col2 = 0 to WIDTH/8) {
        blur_y[row*8 + row2][col*8 + col2] = ...;
      }
      for (col2 = 0 to WIDTH/8) {
        blur_x[row*8 + row2][col*8 + col2] = ...;
      }
    }
  }
}
```

Function Schedules Can Be Configured

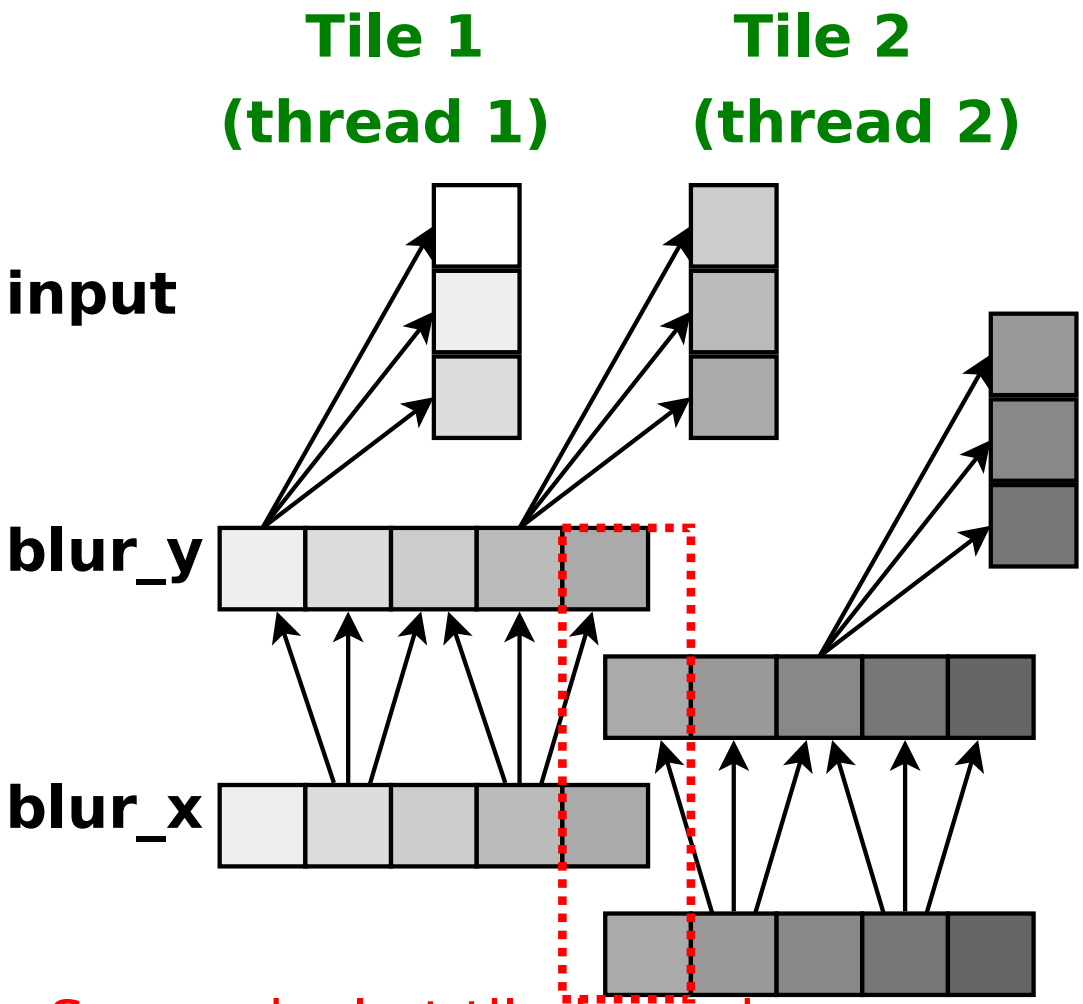
```
blur_x.tile(x, y, x2, y2, 8, 8).parallel(x, y);
blur_y.store_at(blur_x, x).compute_at(blur_x, y2);

float blur_x[HEIGHT][WIDTH];
PARALLEL for (row = 0 to 8) {   // Good parallelism
  PARALLEL for (col = 0 to 8) {
    float blur_y[HEIGHT/8][WIDTH/8];   // Low memory usage
    for (row2 = 0 to WIDTH/8) {
      for (col2 = 0 to WIDTH/8) {   // Good locality
        blur_y[row*8 + row2][col*8 + col2] = ...;
      }
      for (col2 = 0 to WIDTH/8) {
        blur_x[row*8 + row2][col*8 + col2] = ...;
      }
    }
  }
}
```

Tiling Helps Parallelism and Locality



Tiling Helps Parallelism and Locality



Same pixel at tile boundary
- Some work is duplicated

Dynamic Scheduling

Static vs Dynamic Data Dependencies

Avoiding duplicate work when tiling relies on **static data dependencies**.

- In 3x3 blur, max distance from output to input location was 1.

However, some algorithms compute which pixels to read from dynamically.

- Patch-match
- Edge detection

Which input pixels each output pixel will need to compute (the **vector field**) is not known until runtime.

Dynamic Vector Field Example

Original image

Dynamic Vector Field Example

Original image

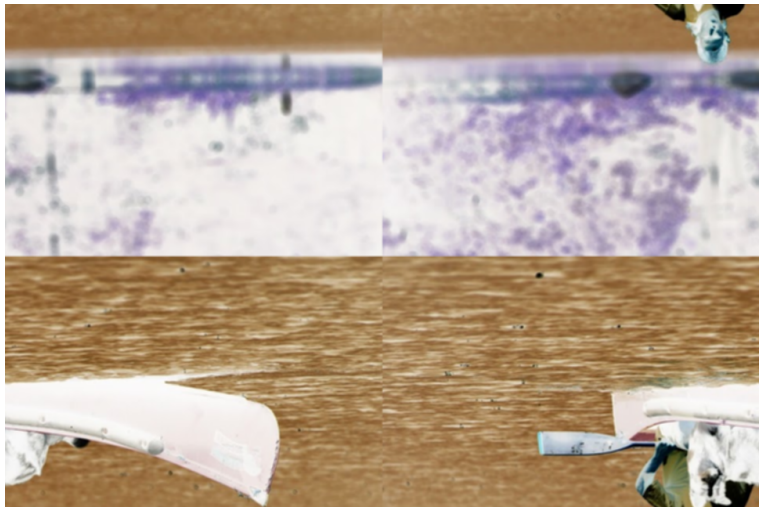
Invert colours

Dynamic Vector Field Example

Original image

Invert colours

Flip & Blur

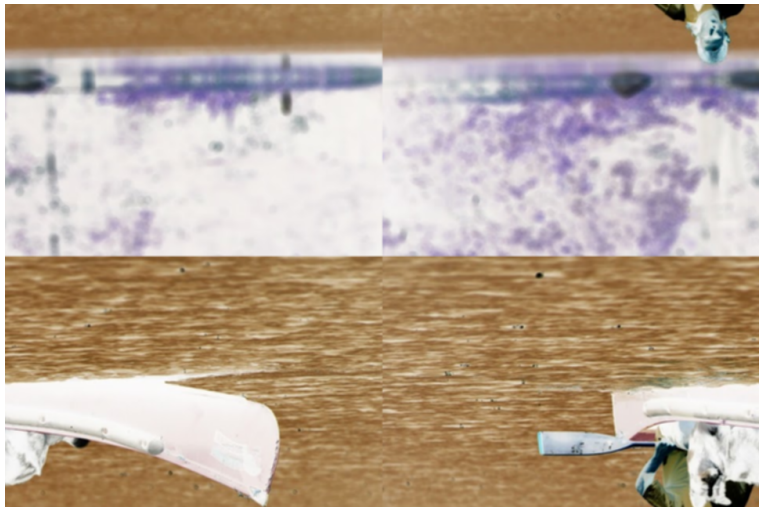


Dynamic Vector Field Example

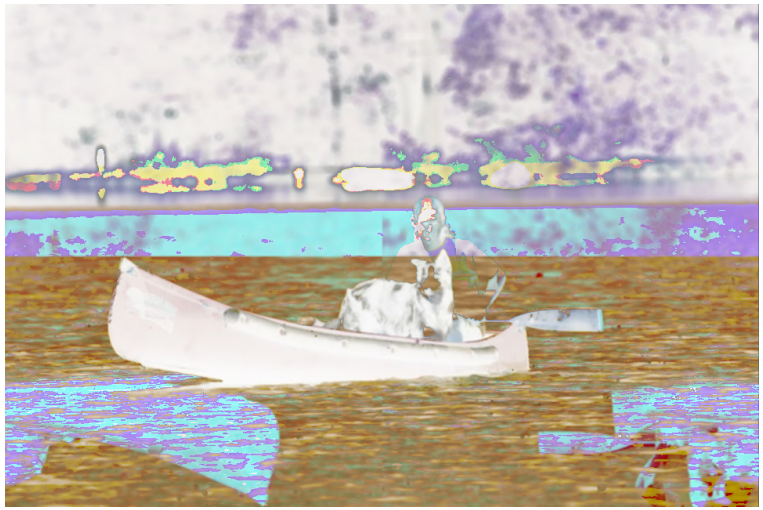
Original image

Invert colours

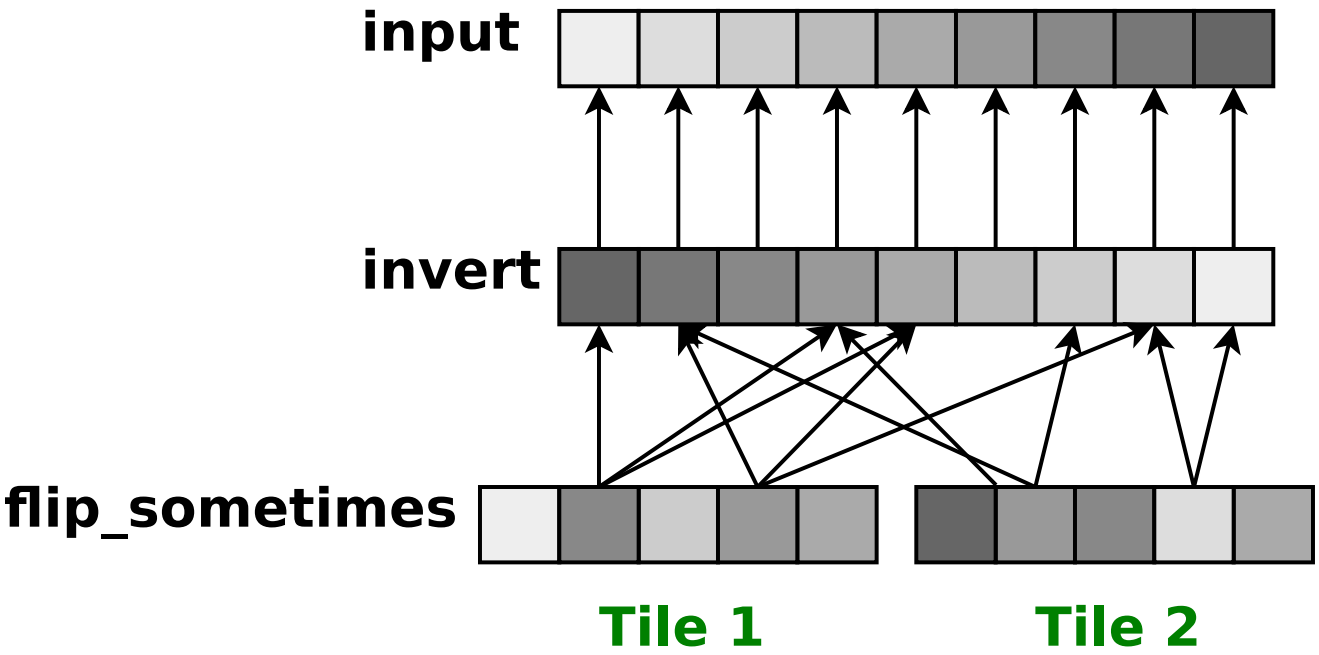
Flip & Blur



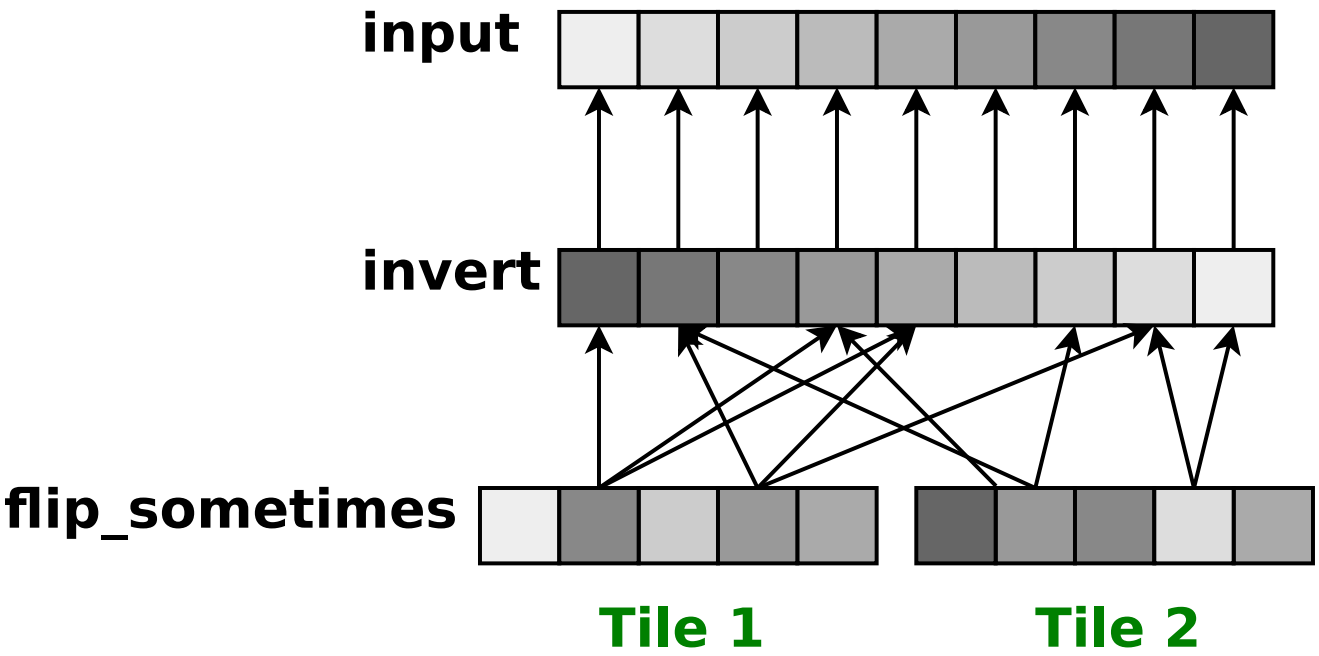
Flip conditionally by colour of pixel



Dynamic Vector Fields Cause Duplicate Work



Dynamic Vector Fields Cause Duplicate Work



Goal: When tile 1 computes `invert()` on a pixel, **remember it** for tile 2.

Solution: Caching Computed Results

Generated code, before:

```
for (tile = ...) {   // Work duplicated across iterations
  for (row = ...)  {
    for (col = ...)  {

        inverted[row][col] = ...;


    }
  }
  (...  compute flipped ...)
}
```

Solution: Caching Computed Results

Generated code, after:

```
bool result_computed[...];
for (tile = ...) {   // Work cached across iterations
  for (row = ...)  {
    for (col = ...)  {
      if (!result_computed[row][col]) {
        inverted[row][col] = ...;
        result_computed[row][col] = true;
      }
    }
  }
  (...  compute flipped ...)
}
```

Evaluation

Evaluation

Evaluation Questions

- How much duplicate work does this let us avoid?
- How do different tilings, etc. affect savings?

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- How much duplicate work does this let us avoid?
- How do different tilings, etc. affect savings?

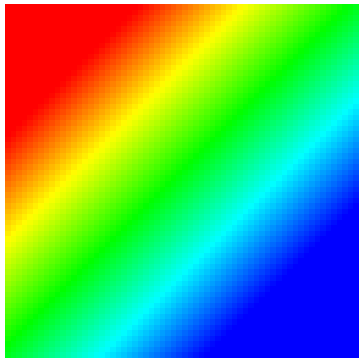
Approach

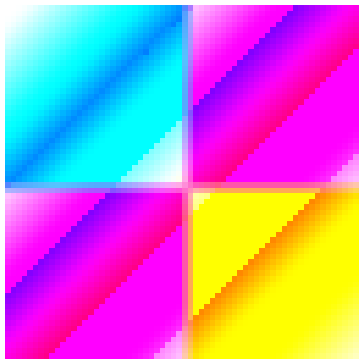
- Used the transformation from the example
  - (stage 1 `invert`, stage 2 `flip_and_blur`)
- Measured # of calls to `invert` and execution time
- Tested with several different function schedules

Experimental Setup

Ran experiments using small, medium, and large images

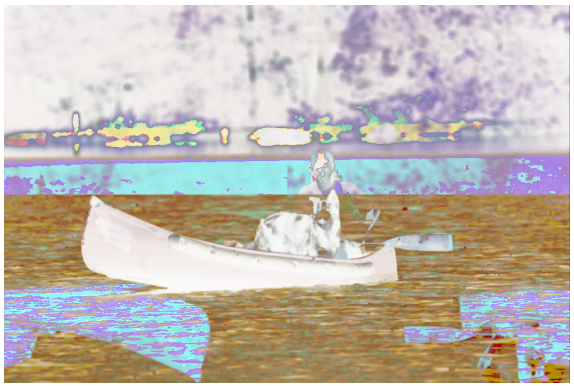
64 x 64





400 x 261

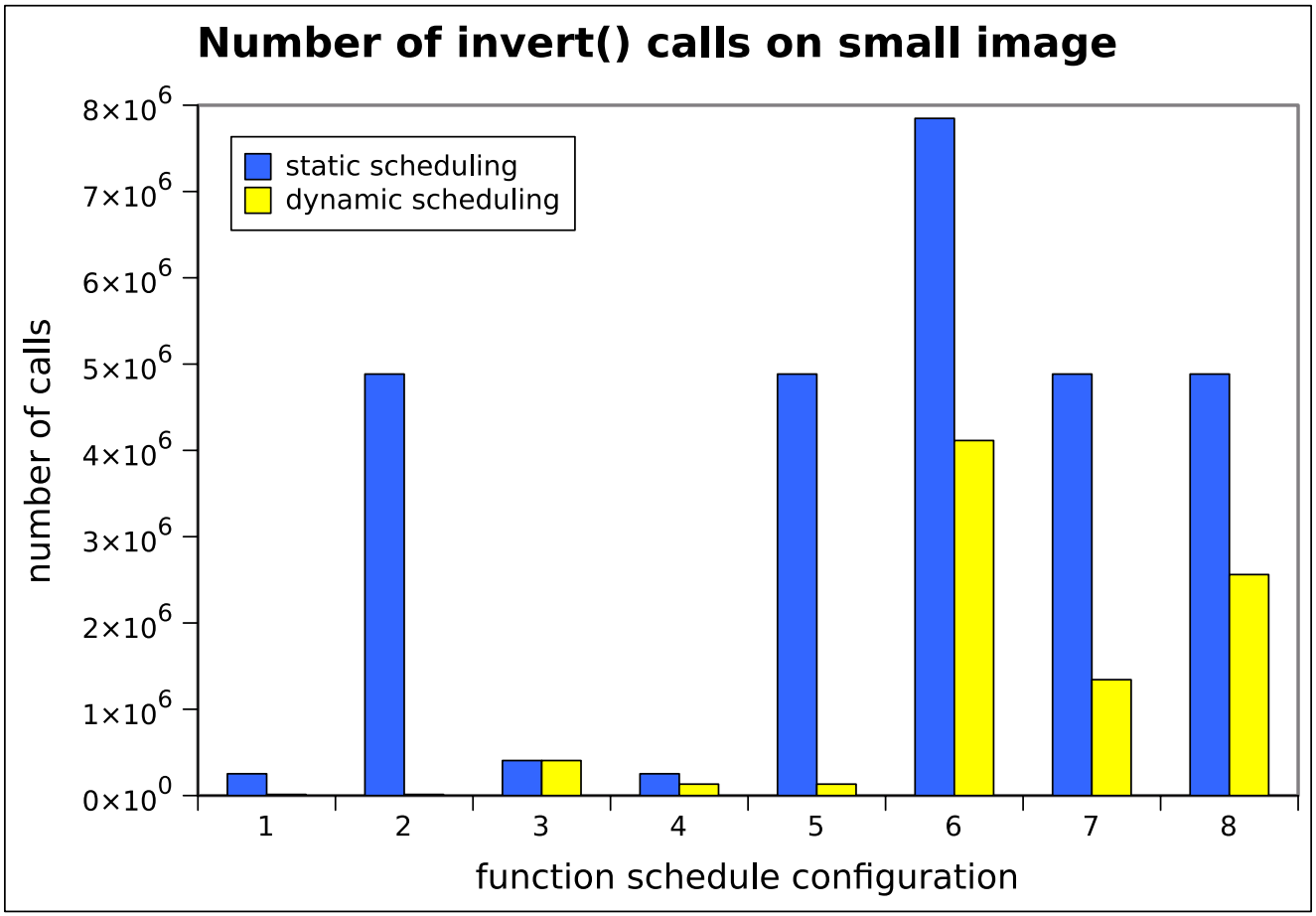
963 x 642



Result: Dynamic Scheduling Saves Computation

For small image, measured number of `invert()` calls during execution

- (think: number of "cache misses")



Conclusion

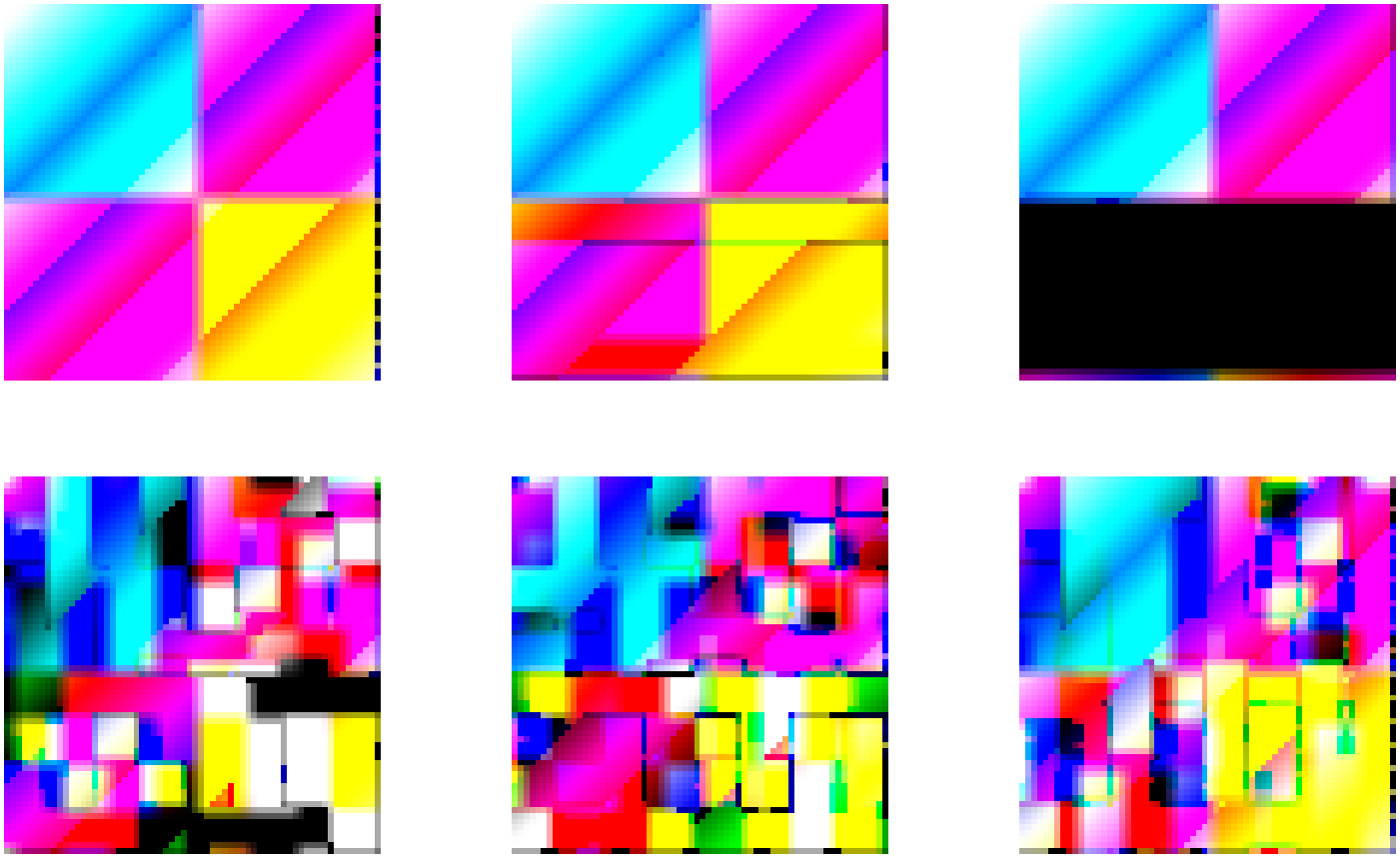
Summary

Halide separates **algorithm logic** from **function scheduling**.

Schedules are influenced by **data dependencies** between algorithm stages.

Dynamically caching results can succeed where static reasoning fails.

Questions?



("bloopers" produced during debugging)

Bonus Slides

Open Questions

Can we cache results at **tile granularity** instead of **pixel granularity**?

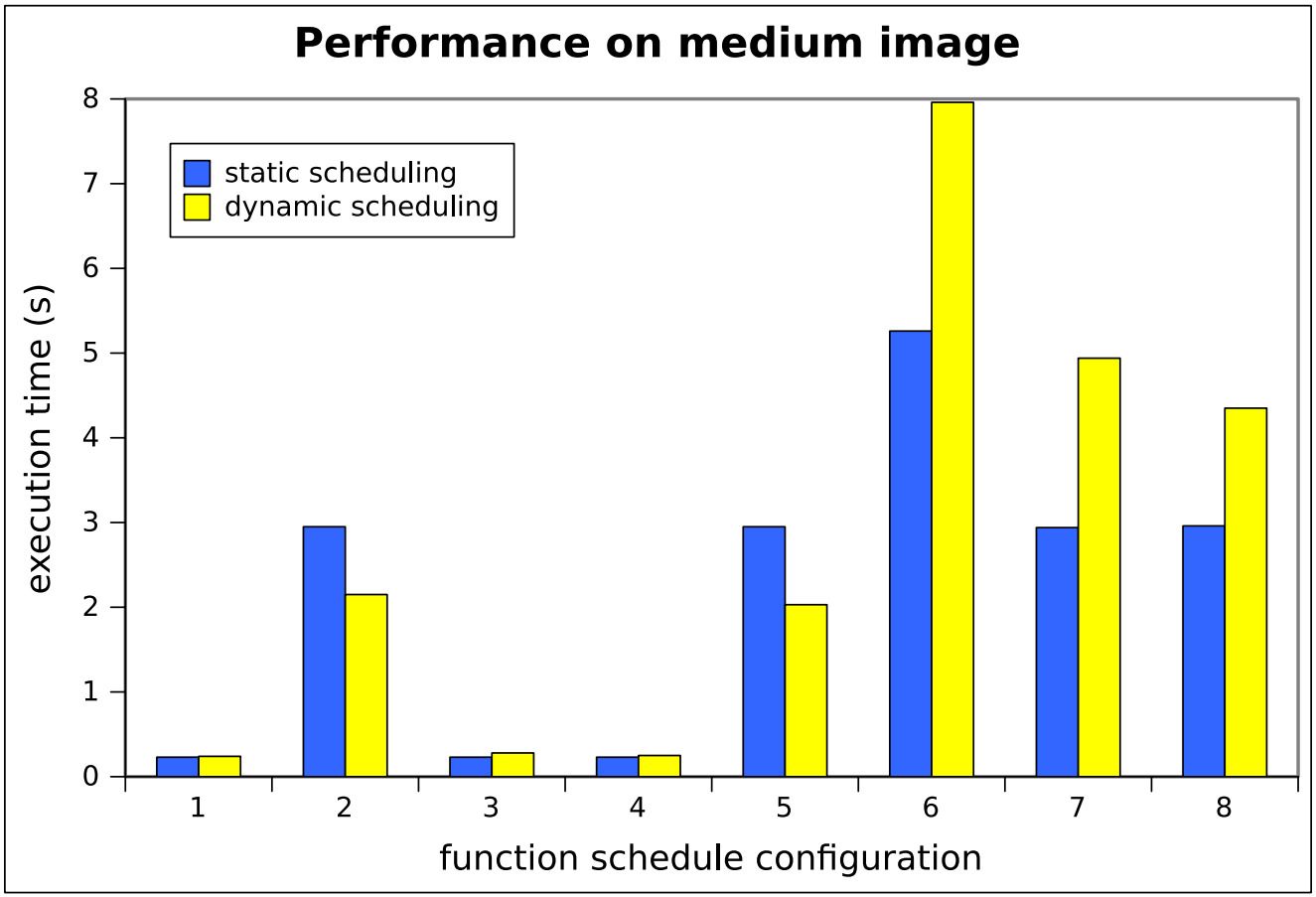
- (Not straightforwardly. Sizes and shapes of tiles change across iterations of outer loops. Need more runtime support.)

With **parallel loops**, where do we need memory barriers?

- (And how does multithreading affect work deduplication?)

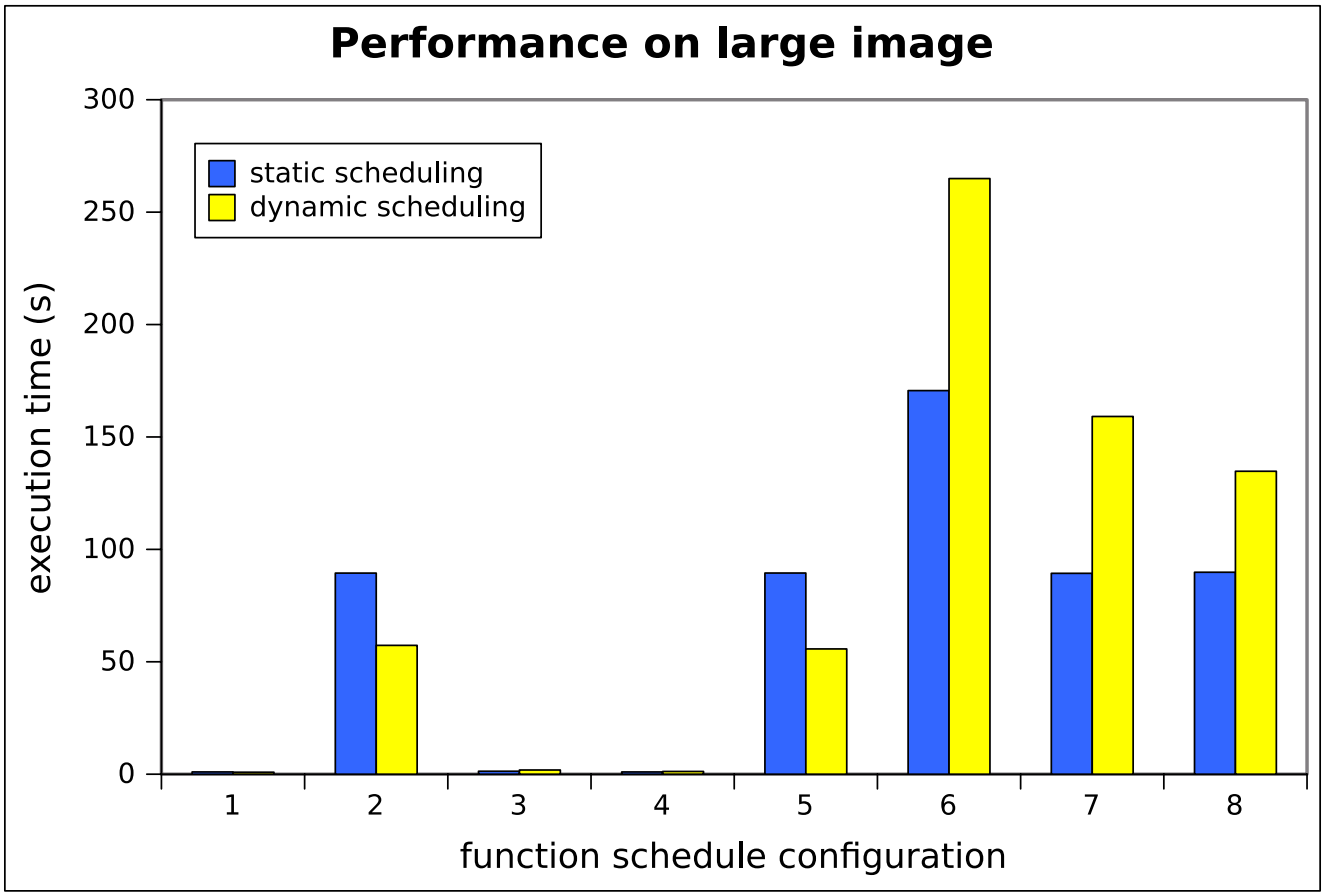
Result: Dynamic Scheduling Saves Time (sometimes...)

For medium and large images, measured execution time



Result: Dynamic Scheduling Saves Time (sometimes...)

For medium and large images, measured execution time



Which function schedules did I use?

```
flipped.tile(x, y, xi, yi, 2, 2);
```

Which function schedules did I use?

```
flipped.tile(x, y, xi, yi, 2, 2);
```

- `inverted.store_at(c)`
  - `.compute_at(y);` (not included)
  - `.compute_at(x);` (not included)
  - `.compute_at(yi);` (#1)
  - `.compute_at(xi);` (#2)
- `inverted.store_at(y)`
  - `.compute_at(x);` (#3)
  - `.compute_at(yi);` (#4)
  - `.compute_at(xi);` (#5)
- `inverted.store_at(x)`
  - `.compute_at(yi);` (#6)
  - `.compute_at(xi);` (#7)
- `inverted.store_at(yi)`
  - `.compute_at(xi);` (#8)