CSE211: Compiler Design

Nov. 22, 2023

- **Topic**: Loop structure and DSLs

- **Discussion questions**:
  - *Lots of discussions throughout about loops and DSLs*

from: https://people.csail.mit.edu/sparis/publi/2011/siggraph/

Announcements

- Homework 3 is out
  - Due on Nov. 29 (1.5 weeks to do it)
  - You should have a partner. If not, let me know ASAP
  - I'll try to have office hours on Monday
- Start thinking about 2nd paper
- Final Project Getting close to the deadline to getting it approved
  - Approved by Monday(Nov. 27)!
  - Presentations must be ready by Dec. 6
  - Deadline is to get final project APPROVED, not start brainstorming
  - I won't be answering piazza during the holiday
- One more homework assigned when HW 3 is due

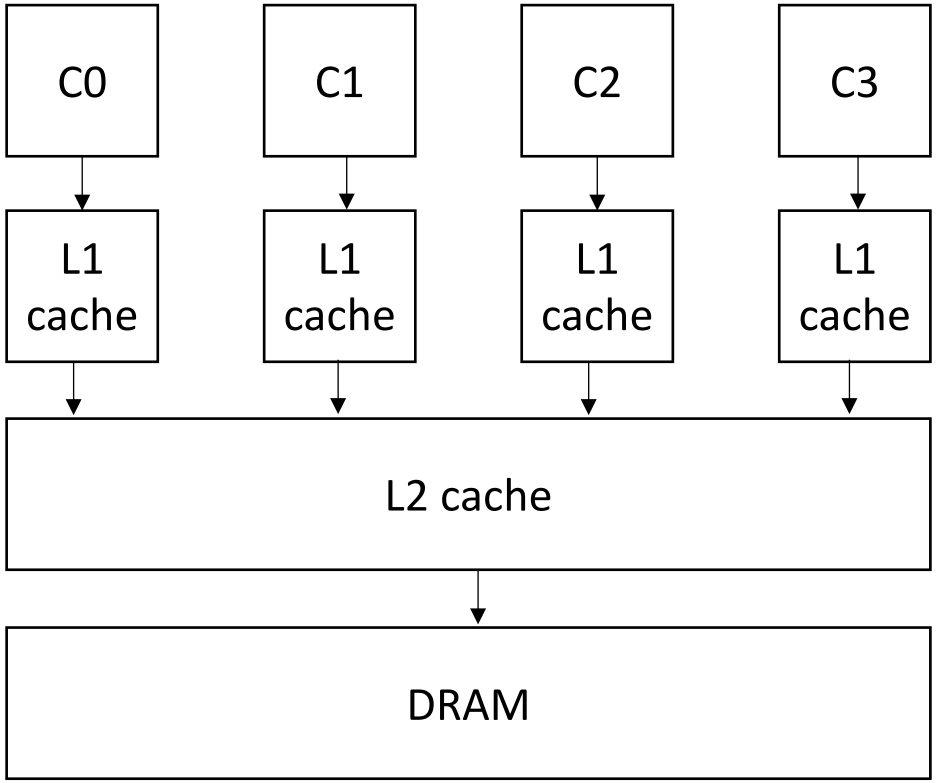
Announcements

- HW 2 is graded, please let us know if there are issues ASAP

Review

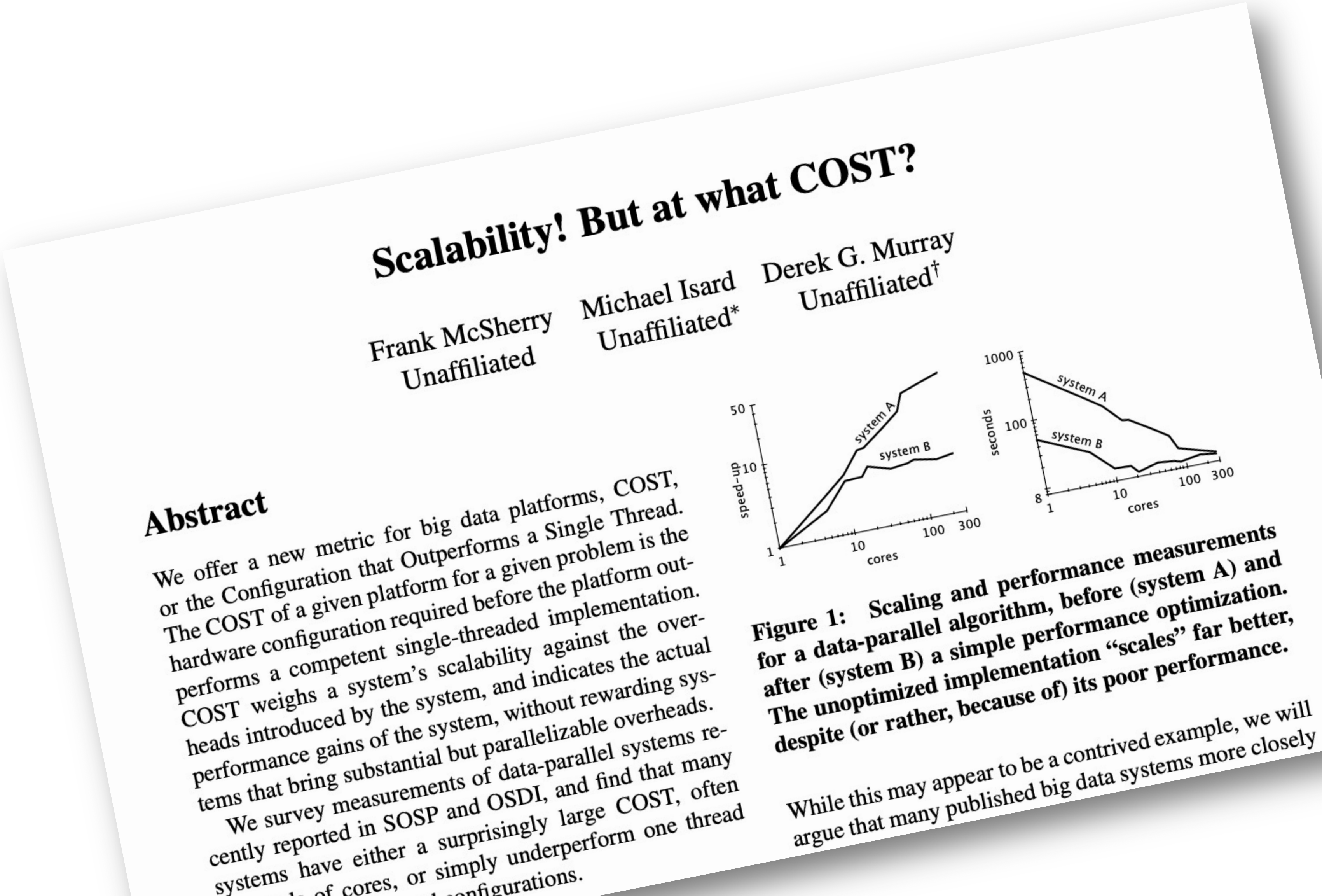
Shifting our focus back to a single core

- We need to consider single threaded performance
- Good single threaded performance can enable better parallel performance
  - **Memory locality** is key to good parallel performance.



Shifting our focus back to a single core

- Why?



Scalability! But at what COST?

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Unaffiliated*

Derek G. Murray
Unaffiliated†

Abstract

We offer a new metric for big data platforms, COST, or the Configuration that Outperforms a Single Thread. The COST of a given platform for a given problem is the hardware configuration required before the platform outperforms a competent single-threaded implementation. COST weighs a system's scalability against the overheads introduced by the system, and indicates the actual performance gains of the system, without rewarding systems that bring substantial but parallelizable overheads.

We survey measurements of data-parallel systems recently reported in SOSP and OSDI, and find that many systems have either a surprisingly large COST, often ... of cores, or simply underperform one thread ... configurations.

Figure 1: Scaling and performance measurements for a data-parallel algorithm, before (system A) and after (system B) a simple performance optimization. The unoptimized implementation "scales" far better, despite (or rather, because of) its poor performance.

While this may appear to be a contrived example, we will argue that many published big data systems more closely

Transforming Loops

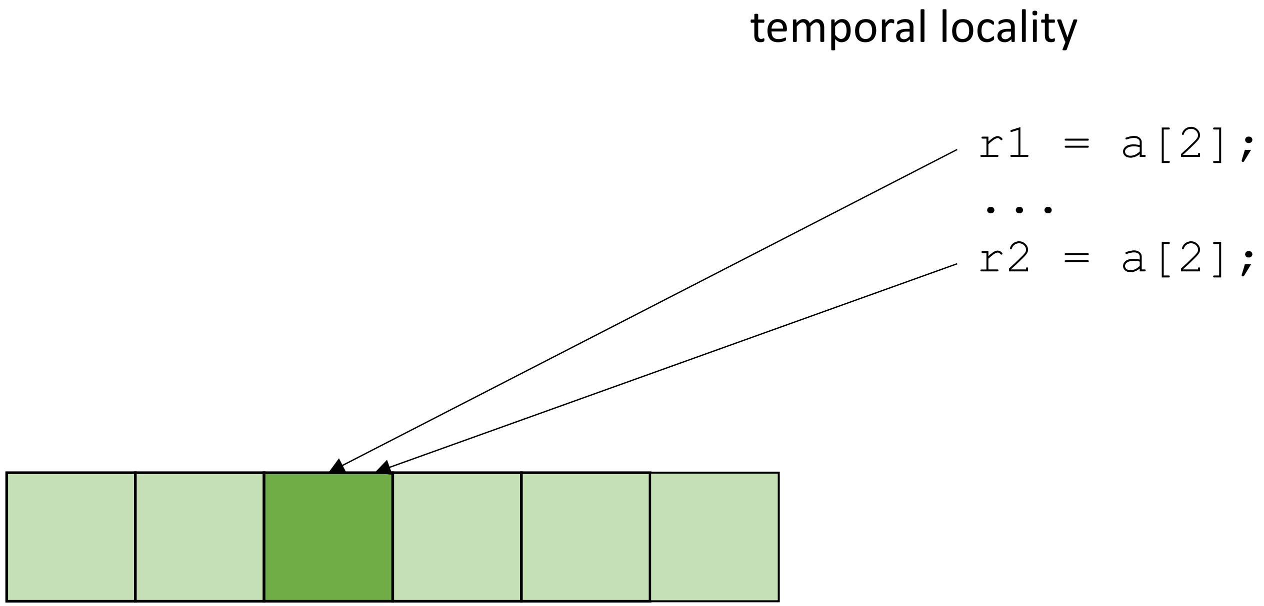
- Locality is key for good (parallel) performance:

- What kind of locality are we talking about?

Transforming Loops

- Locality is key for good parallel performance:

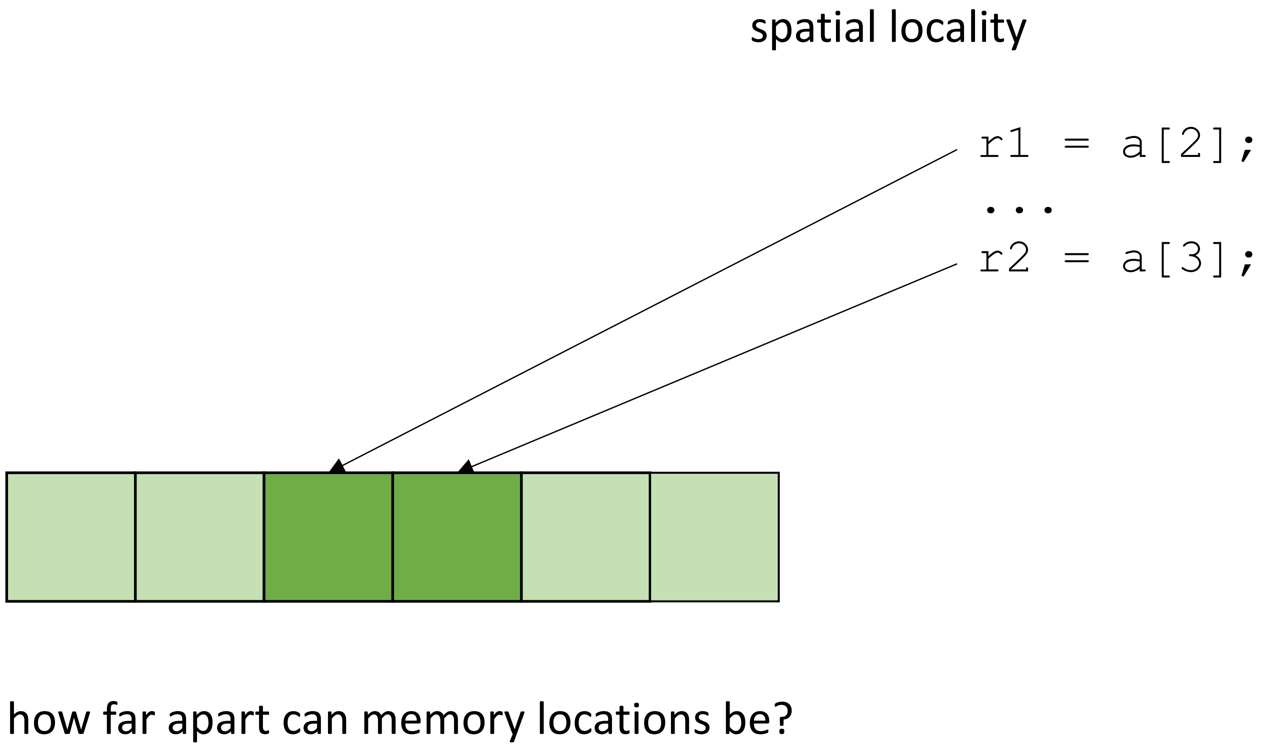
- Two types of locality:
  - Temporal locality
  - Spatial locality



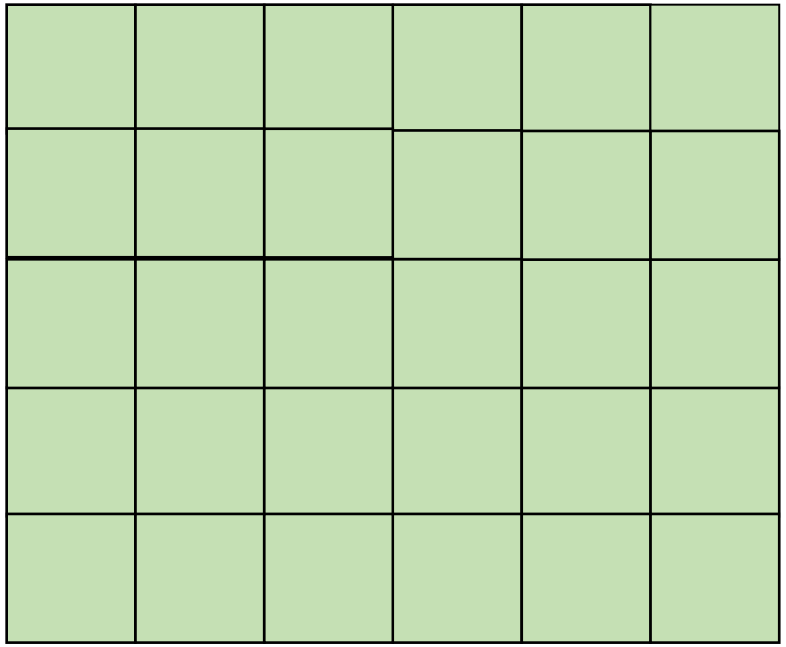
Transforming Loops

- Locality is key for good parallel performance:

- Two types of locality:
  - Temporal locality
  - Spatial locality

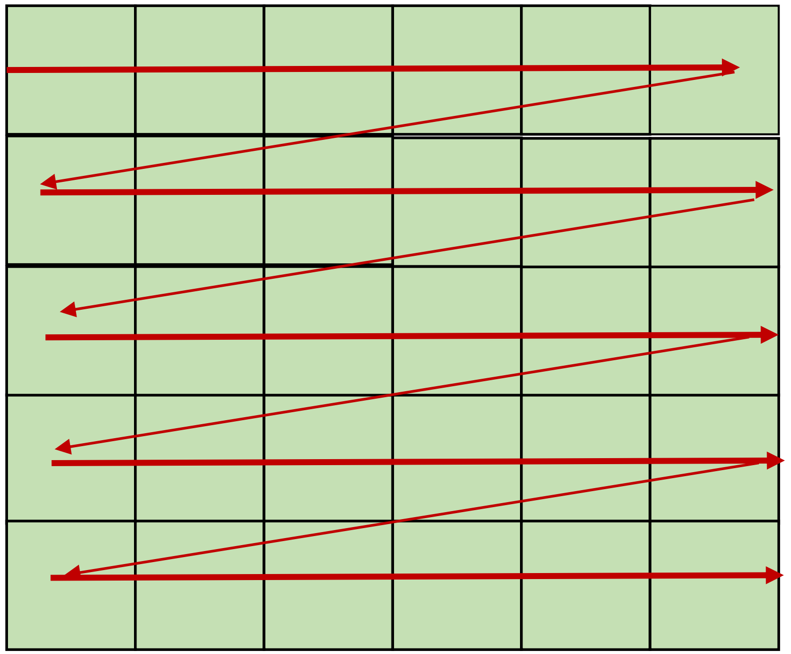


How multi dimensional arrays are stored:



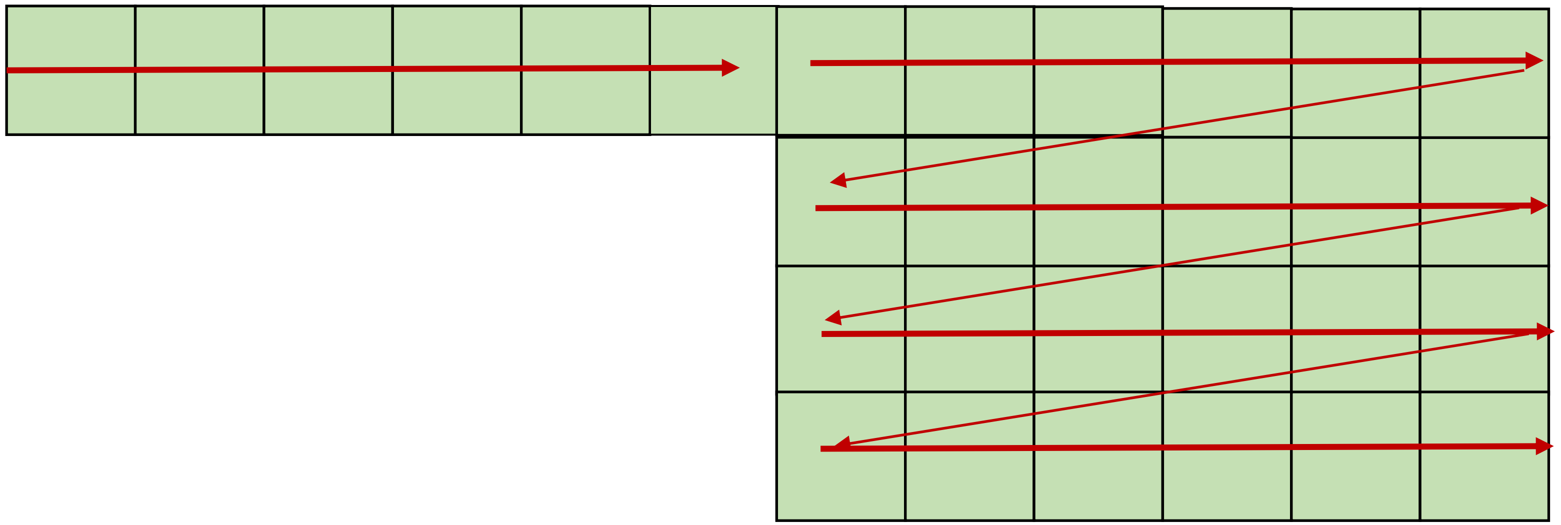
How multi dimensional arrays are stored:

Row major



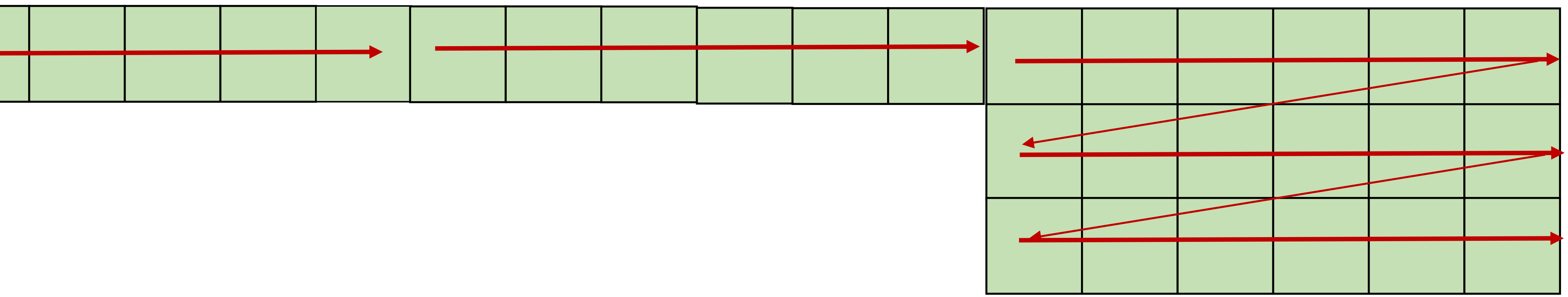
How multi dimensional arrays are stored:

Row major



How multi dimensional arrays are stored:

Row major

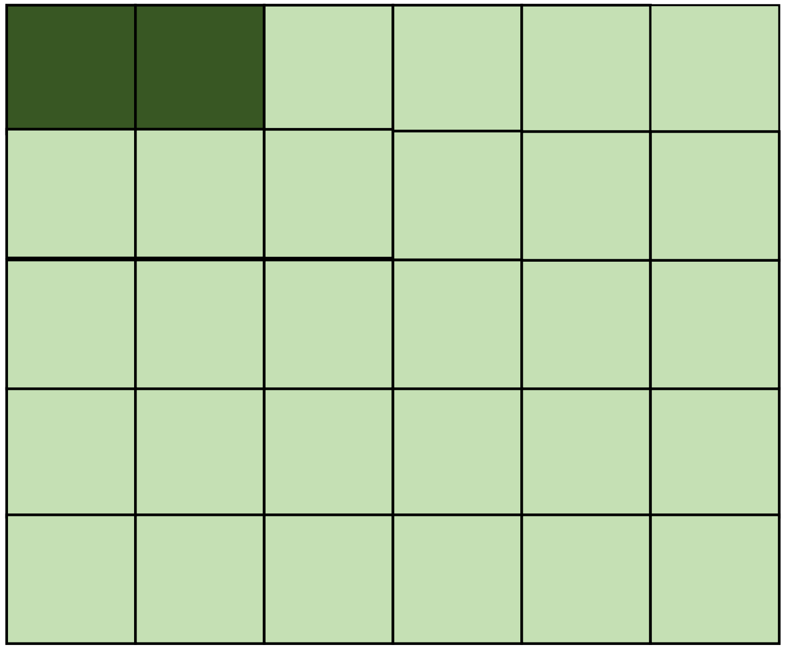


How multi dimensional arrays are stored:

say x == y == 0

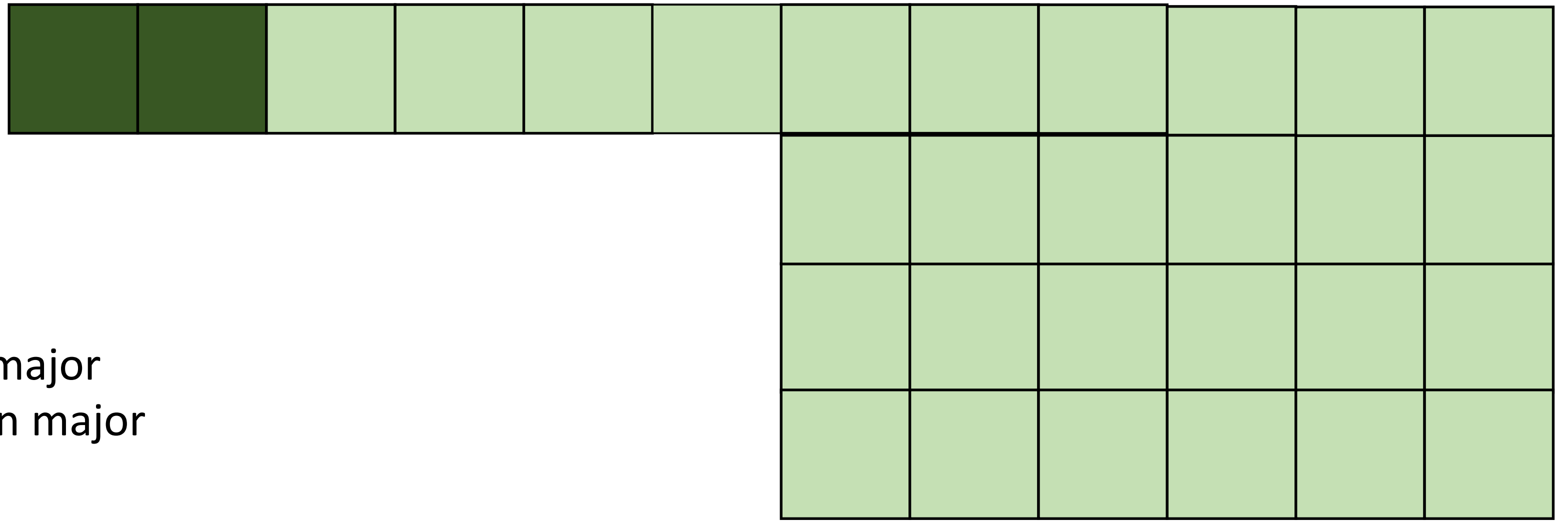
```
x1 = a[x,y];
x2 = a[x, y+1];
```

good pattern for row major
bad pattern for column major



How multi dimensional arrays are stored:

unrolled row major: still has locality



```
x1 = a[x,y];
x2 = a[x, y+1];
```

good pattern for row major
bad pattern for column major

How much does this matter?

```
for (int x = 0; x < x_size; x++) {
  for (int y = 0; y < y_size; y++) {
        a[x,y] = b[x,y] + c[x,y];
   }
}
```

```
for (int y = 0; y < y_size; y++) {
  for (int x = 0; x < x_size; x++) {
        a[x,y] = b[x,y] + c[x,y];
   }
}
```

which will be faster?
by how much?

Demo

Dependent loop bounds example:

```
for (y = 0; y <= 5; y++) {
  for (x = y; x <= 7; x++) {
    a[x,y] = b[x,y] + c[x,y];
  }
}
```

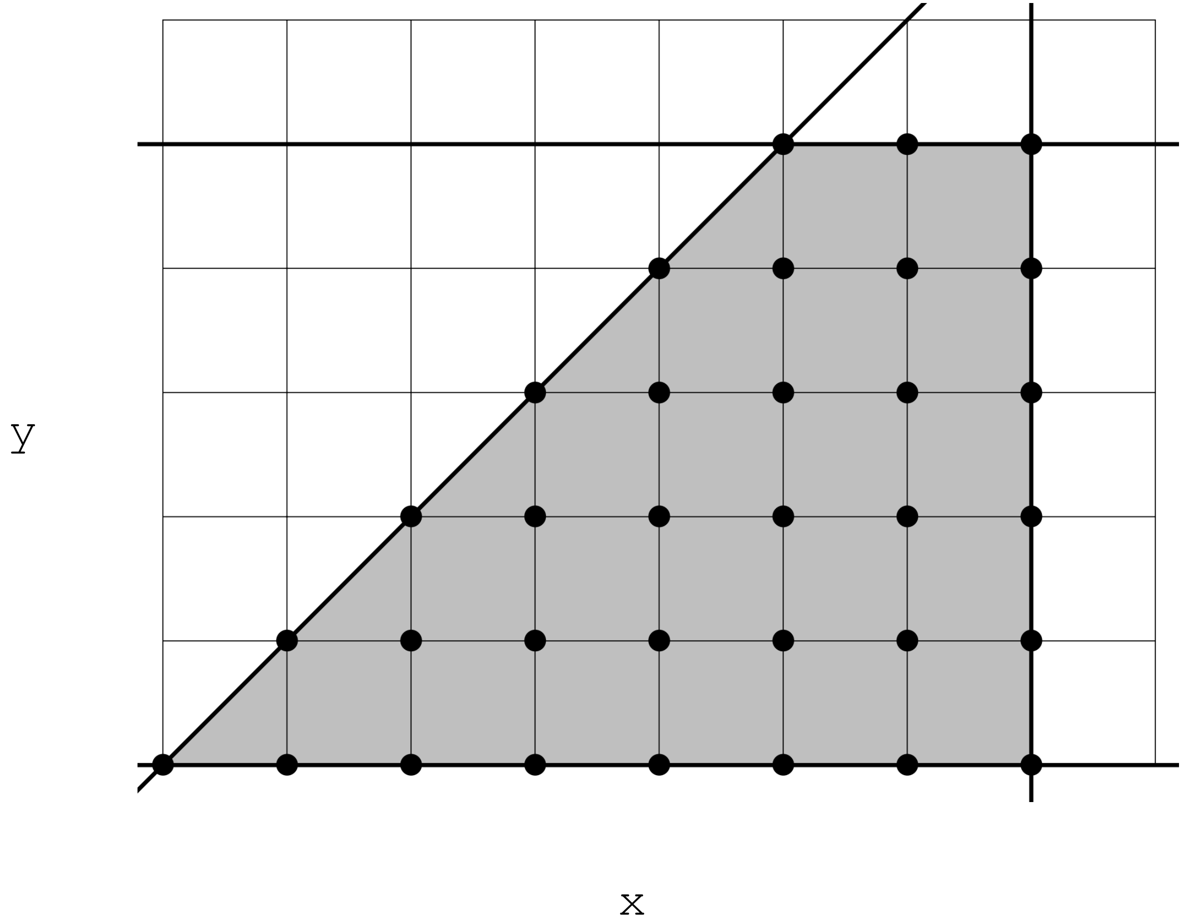
Dependent loop bounds example:

```
for (x = 0; x <= 7; x++) {
  for (y = 0; y <= min(x,5); y++) {
    a[x,y] = b[x,y] + c[x,y];
  }
}
```

x loop constraints without y:

```
x >= 0
x <= 7

y loop constraints:
y >= 0
y <= min(x,5)
```



New material

Recap what we’ve covered with loops

- Are the loop iterations independent?
  - The property holding all of these optimizations together

- mainstream compilers don’t do much to help us out here
  - why not?

- But DSLs can!

Discussion

Discussion questions:

What is a DSL?

What are the benefits and drawbacks of a DSL?

What DSLs have you used?

What is a DSL

- Objects in an object oriented language?
  - operator overloading (C++ vs. Java)
- Libraries?
  - Numpy
- Does it need syntax?
  - Pytorch/Tensorflow

What is a DSL

- Not designed for general computation, instead designed for a domain

- How wide or narrow can this be?
  - Numpy vs TensorFlow
  - Pros and cons of this design?

- Domain specific optimizations
  - Optimizations do not have to work well in all cases

DSL designs

- Ease of expressiveness

```
sed ‘s/Utah/California’ address.txt
```

gnuplot

```
set title ”Parallel timing experiments"
set xlabel ”Threads”
set ylabel ”Speedup"
plot ”data.dat" with lines
```

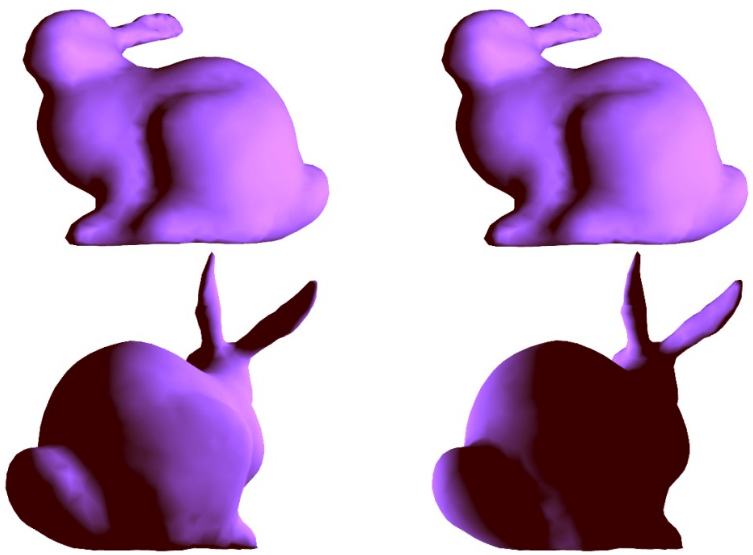
Other examples?

These require their own front end. What about Matplotlib?

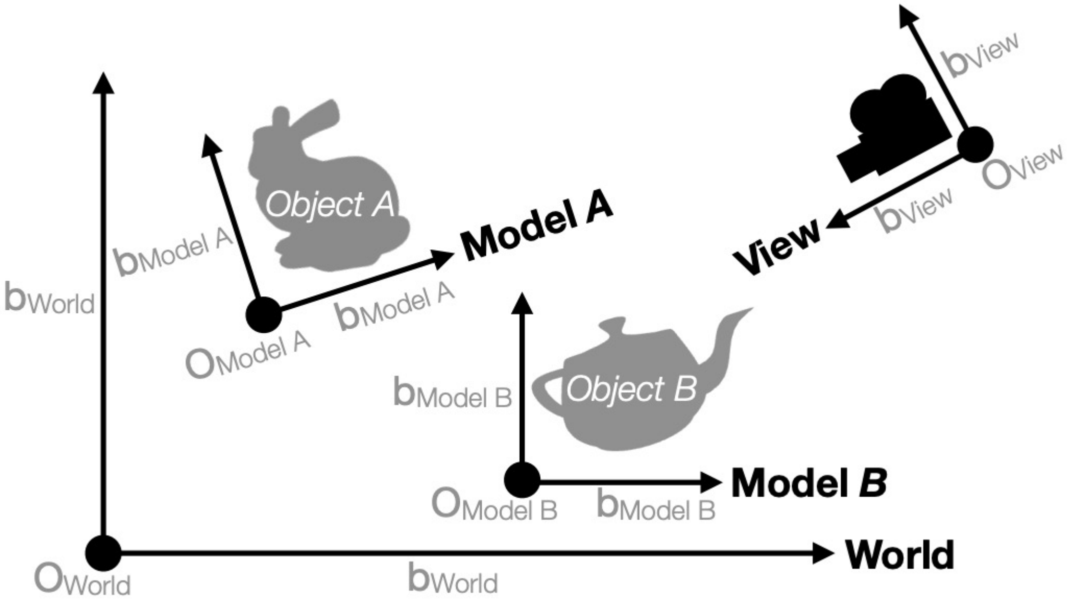
DSL designs

- Ease of expressiveness

make it harder to write bugs!



(a) Correct implementation. (b) With geometry bug.



Add reference tags to types: World or View

From: Geometry Types for Graphics Programming, OOPSLA 2020

DSL designs

- Ease of optimizations

Examples?

From homework 3:

What does this assume?
Optional in C++
Non-optional in Tensorflow

- reduction loops:
  - Entire computation is dependent
  - Typically short bodies (addition, multiplication, max, min)

1	2	3	4	5	6

addition: 21

max: 6

min: 1

Typically faster than implementations in general languages.

DSL designs

- Easier to reason about

Typically much fewer lines of code than implementations in general languages.

gnuplot example again

```
set title ”Parallel timing experiments"
set xlabel ”Threads”
set ylabel ”Speedup"
plot ”data.dat" with lines
```

tensorflow

```
tf.matmul(a, b)
```

What does an optimized matrix multiplication look like?

https://github.com/flame/blis/tree/master/kernels

DSL designs

- Easier to maintain

- *Optimizations and transforms are less general (more targeted).*
- *Less syntax (sometimes no syntax).*
- *Fewer corner cases.*

DSL design

- Recipe for a DSL talk:
  - Introduce your domain
  - Show scary looking optimized code
  - Show clean DLS code
  - Show performance improvement
  - Have a correctness argument

Halide

- A discussion and overview of **Halide:**
  - Huge influence on modern DSL design
  - Great tooling
  - Great paper

- Originally: A DSL for image pipelining:

Brighten example

from: https://halide-lang.org/tutorials/tutorial_lesson_02_input_image.html

Motivation:

pretty straight
forward computation
for brightening

(1 pass over all pixels)

This computation is known as the “Local Laplacian Filter”. Requires visiting all pixels 99 times

We want to be able to do this
fast and efficiently!

Main results in from Halide show a 1.7x speedup with 1/5 the LoC over hand optimized versions at Adobe

from: https://people.csail.mit.edu/sparis/publi/2011/siggraph/

Decoupling computation from optimization

- We love Halide not only because it can make pretty pictures very fast
- We love it because it changed the level of abstraction for thinking about computation and optimization
- (Halide has been applied in many other domains now, turns out everything is just linear algebra)

Example

- in C++

```
for (int x = 0; x < x_size; x++) {
  for (int y = 0; y < y_size; y++) {
        a[x,y] = b[x,y] + c[x,y];
   }
}
```

Which one would you write?

```
for (int y = 0; y < y_size; y++) {
  for (int x = 0; x < x_size; x++) {
        a[x,y] = b[x,y] + c[x,y];
   }
}
```

Optimizations are a black box

- What are the options?
  - -O0, -O1, -O2, -O3
  - Is that all of them?
  - What do they actually do?

https://stackoverflow.com/questions/15548023/clang-optimization-levels

Optimizations are a black box

- What are the options?
  - -O0, -O1, -O2, -O3
  - Is that all of them?
  - What do they actually do?

- ***Answer***: they do their best for a wide range of programs. The common case is that you should not have to think too hard about them.

- ***In practice***, to write high-performing code, you are juggling computation and optimization in your mind!

Halides approach

- Decouple
  - what to compute (the program)
  - with how to compute (the optimizations, also called the schedule)

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for (int y = 0; y < y_size; y++) {
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        a[x,y] = b[x,y] + c[x,y];
   }
}
```

C++:

program

```
add(x,y) = b(x,y) + c(x,y)
```

schedule

```
add.order(x,y)
```

Halide (high-level)

Halides approach

- Decouple
  - what to compute (the program)
  - with how to compute (the optimizations, also called the schedule)

Pros and Cons?

program

```
add(x,y) = b(x,y) + c(x,y)
```

schedule

```
add.order(x,y)
```

Halide (high-level)

Halide optimizations

- Now all of a sudden, the programmer has to worry about how to optimize the program. Previously the compiler compiler made those decisions and we just “helped”.

- What can we do if the optimizations are decoupled?

Halide optimizations

- Auto-tuning
  - automatically select a schedule
  - compile and run/time the program.
  - Keep track of the schedule that performs the best

- Why don't all compilers do this?

Halide optimizations

- Auto-tuning
  - automatically select a schedule
  - compile and run/time the program.
  - Keep track of the schedule that performs the best

- Why don’t all compilers do this?

- Image processing is especially well-suited for this:
  - Images in different contexts might have similar sizes (e.g. per phone, on twitter, on facebook)

Halide programs

- Halide programs:
  - built into C++, contained within a header

```
#include "Halide.h"
```

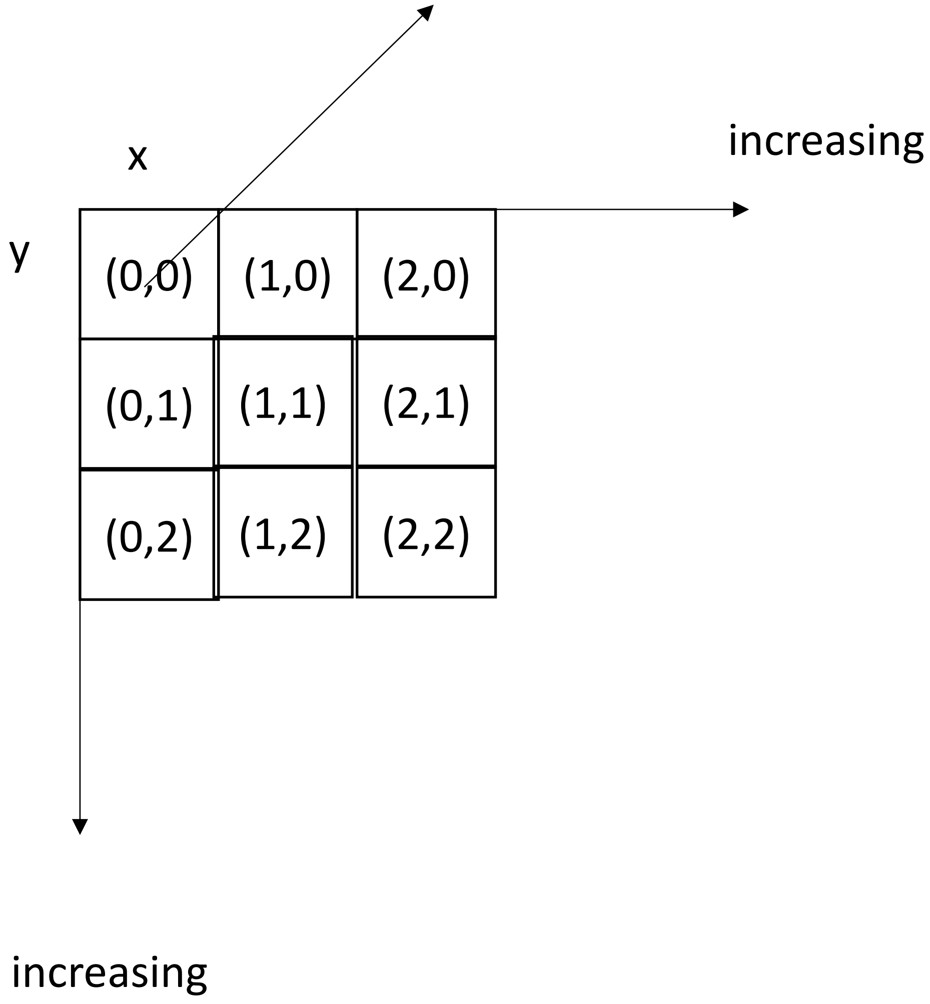
```
Halide::Func gradient;          // a pure function declaration

Halide::Var x, y;               // variables to use in the definition of the function (types?)

gradient(x, y) = x + y;         // the function takes two variables (coordinates in the image) and adds them
```

from: https://halide-lang.org/tutorials/tutorial_lesson_01_basics.html

```
gradient(x, y) = x + y;
```



```
gradient(x, y) = x + y;
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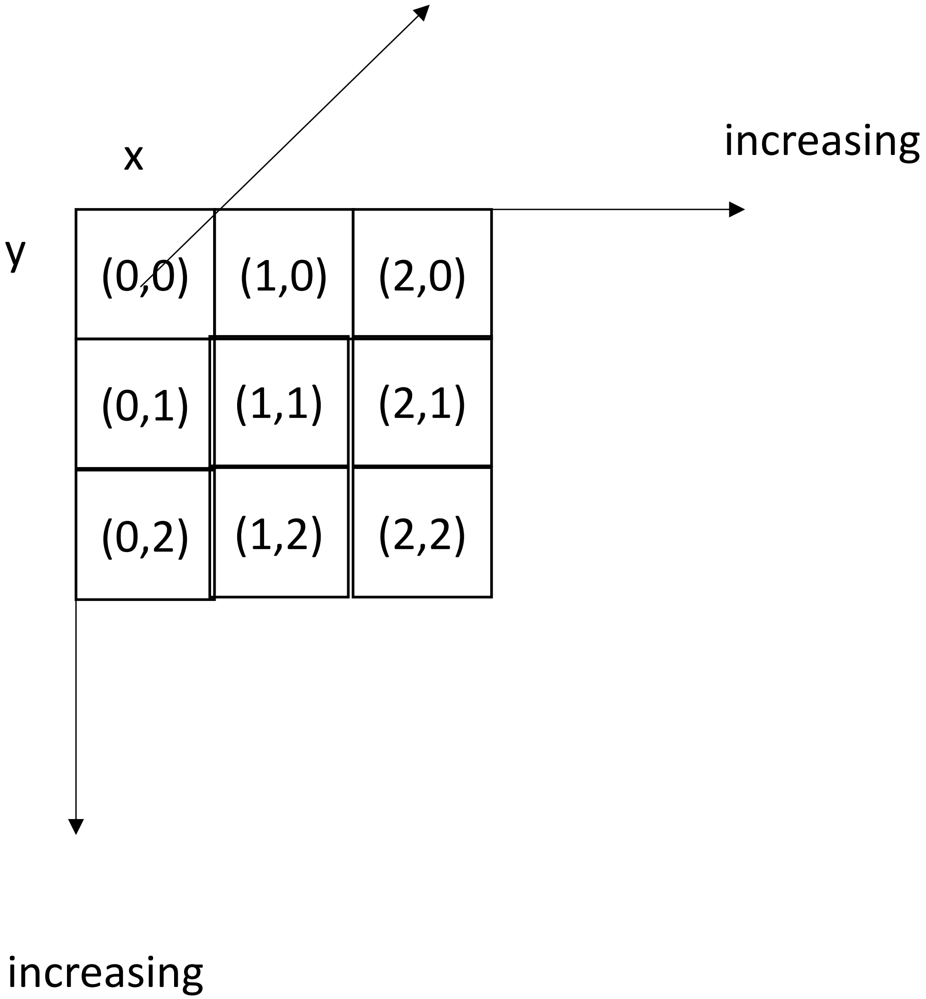
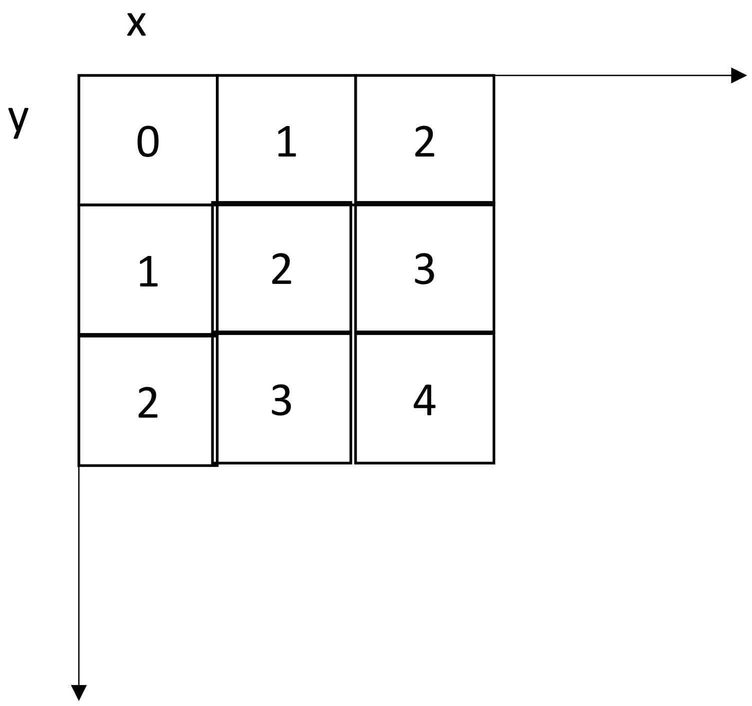
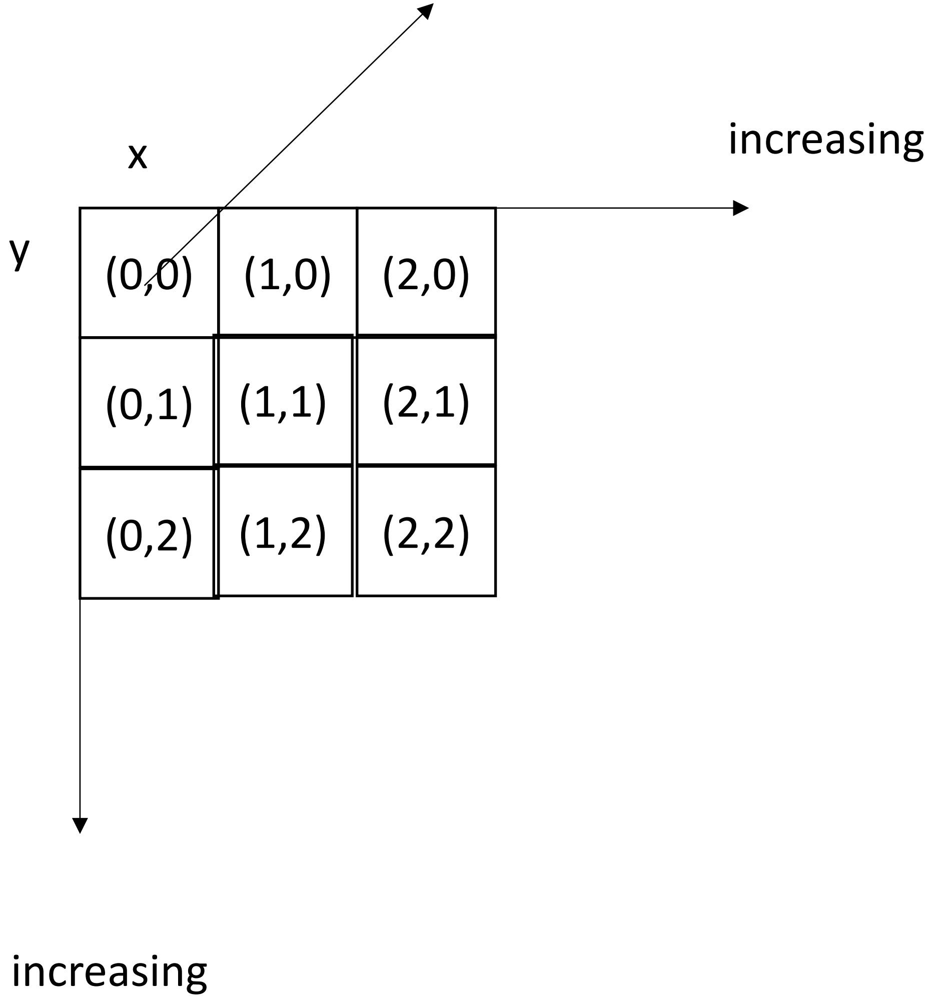


after applying the gradient function



what are some properties of this computation?

```
gradient(x, y) = x + y;
```



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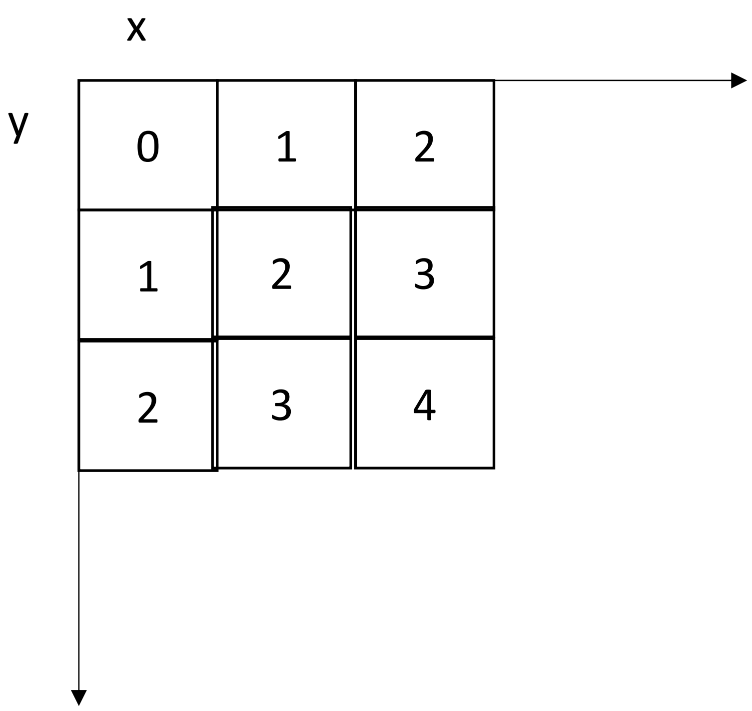
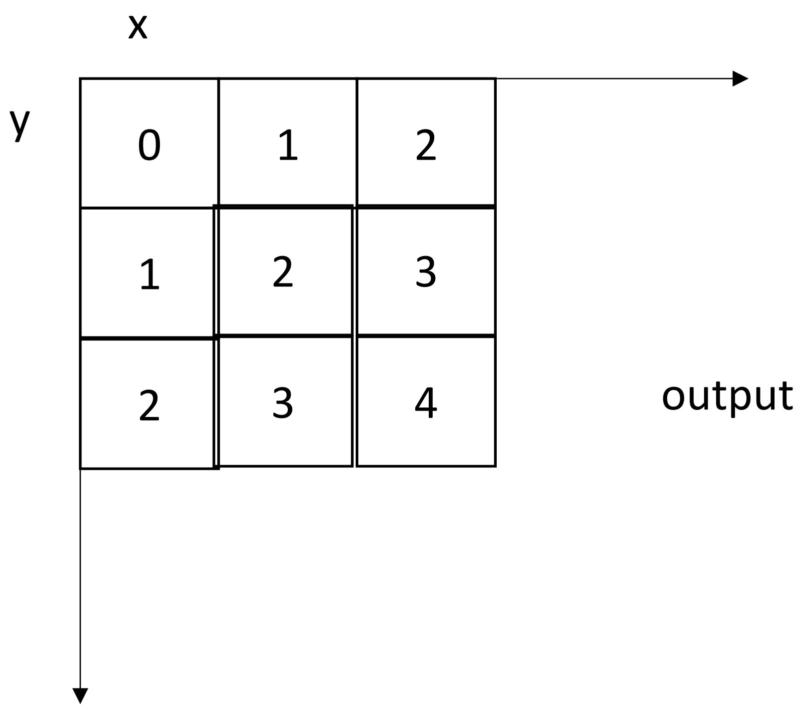


what are some properties of this computation?
Data races?
Loop indices and increments?
The order to compute each pixel?

Executing the function

```
Halide::Buffer<int32_t> output = gradient.realize({3, 3});
```

Not compiled until this point
Needs values for x and y



Example: brightening

Brighten example

```cpp
Halide::Buffer<uint8_t> input = load_image("parrot.png");

Halide::Func brighter;

Halide::Expr value = input(x, y, c);

value = Halide::cast<float>(value);

value = value * 1.5f;

value = Halide::min(value, 255.0f);

value = Halide::cast<uint8_t>(value);

brighter(x, y, c) = value;

Halide::Buffer<uint8_t> output =
               brighter.realize({input.width(), input.height(), input.channels()});
```

```cpp
Halide::Buffer<uint8_t> input = load_image("parrot.png");

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brighter(x, y, c) = value;

Halide::Buffer<uint8_t> output =
               brighter.realize({input.width(), input.height(), input.channels()});
```
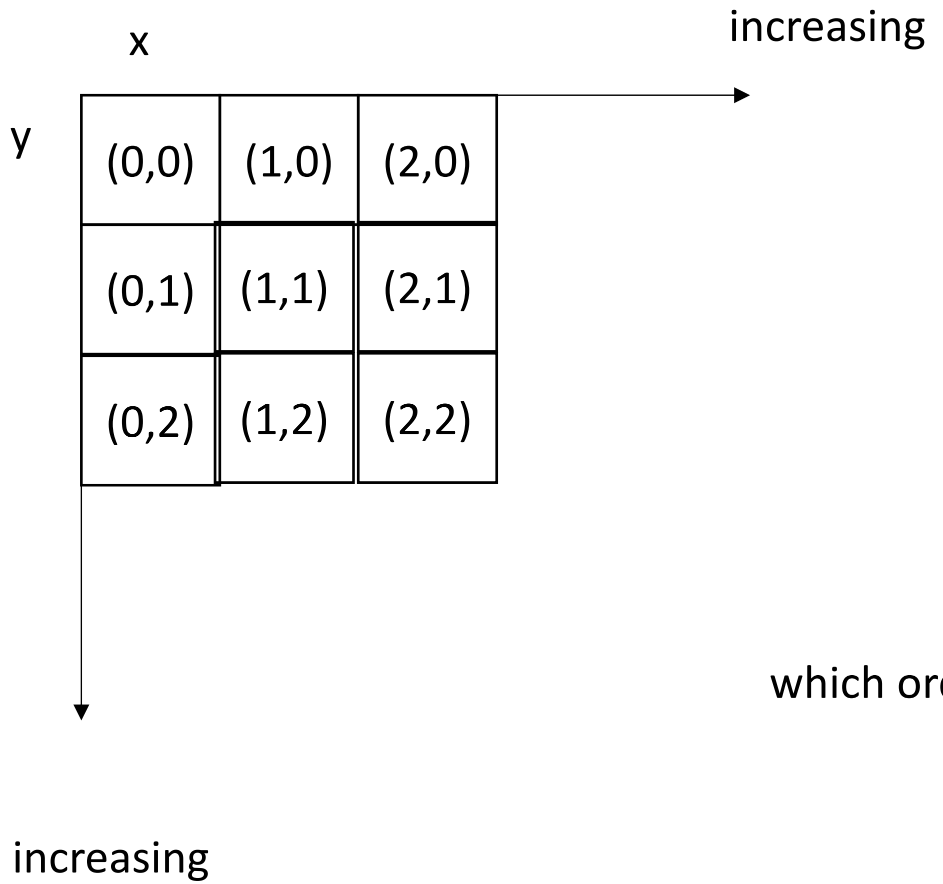

```cpp
brighter(x, y, c) = Halide::cast<uint8_t>(min(input(x, y, c) * 1.5f, 255));
```

Schedules

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({3, 3});
```



which order to traverse these elements?

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({4, 4});
```

```
for (int y = 0; y < 4; y++) {
    for (int x = 0; x < 4; x++) {
        output[y,x] = x + y;
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
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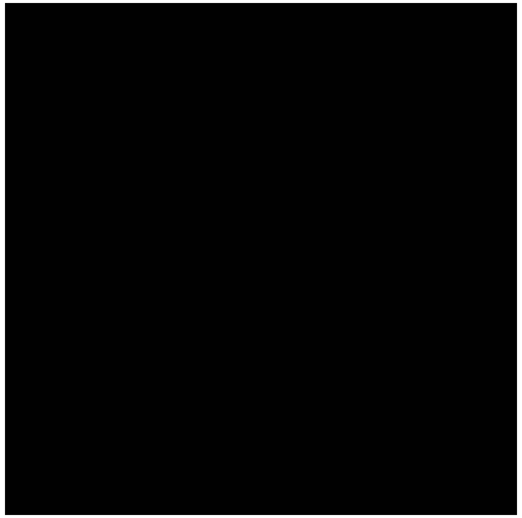

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```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({4, 4});
```

Schedule

```
gradient.reorder(y, x);
```

```
for (int x = 0; x < 4; x++) {
    for (int y = 0; y < 4; y++) {
        output[y,x] = x + y;
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
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Schedule

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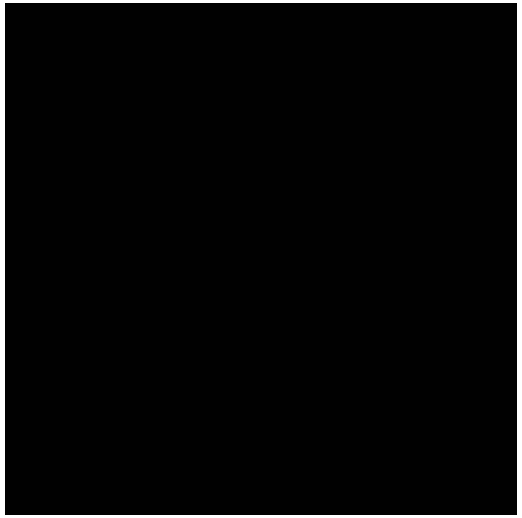

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}
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```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({4, 4});
```

Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 2);
```

```
for (int y = 0; y < 4; y++) {
    for (int x_outer = 0; x_outer < 2; x_outer++) {
        for (int x_inner = 0; x_inner < 2; x_inner++) {
            x = x_inner + x_outer * 2;
            output[y,x] = x + y;
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
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```

Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 2);
```

```
for (int y = 0; y < 4; y++) {
    for (int x_outer = 0; x_outer < 2; x_outer++) {
        for (int x_inner = 0; x_inner < 2; x_inner++) {
            x = x_outer*2 + x_inner;
            output[y,x] = x + y;
        }
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({4, 4});
```

Schedule

```
Var xy;
gradient.fuse(x, y, xy);
```

```
for (int xy = 0; xy < 4*4; xy++) {
    x = ?
    y = ?
    output[y,x] = x + y;

}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({4, 4});
```

Schedule

```
Var xy;
gradient.fuse(x, y, xy);
```

```
for (int xy = 0; xy < 4*4; xy++) {
    y = xy / 4;
    x = xy % 4;
    output[y,x] = x + y;
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

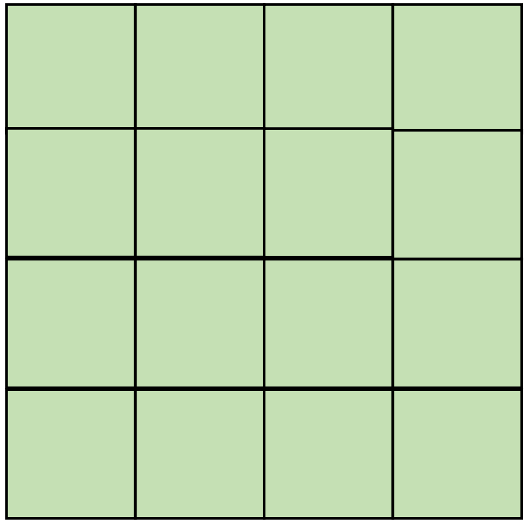
Tiling

Adding loop nestings

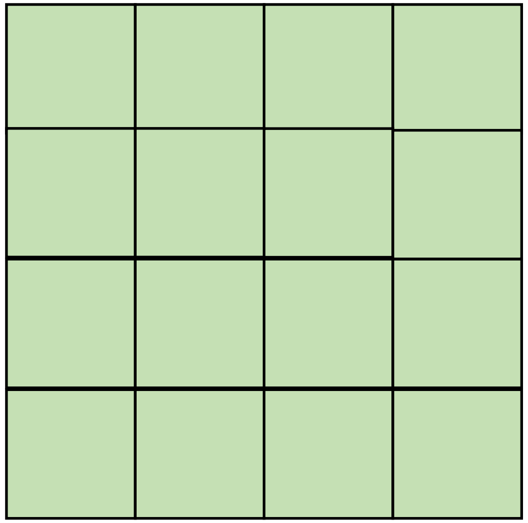
- In some cases, there might not be a good nesting order for all accesses:

$$A = B + C^T$$

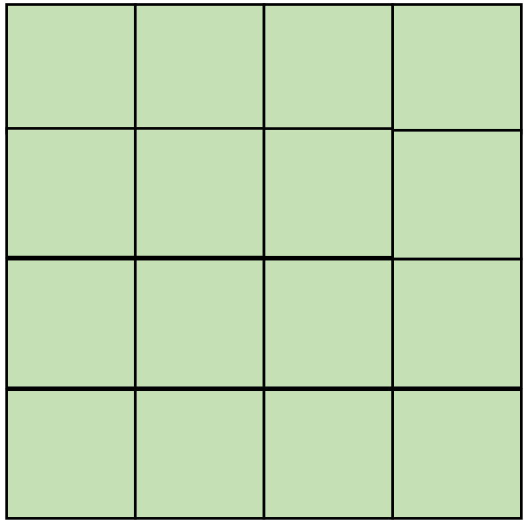
A



B



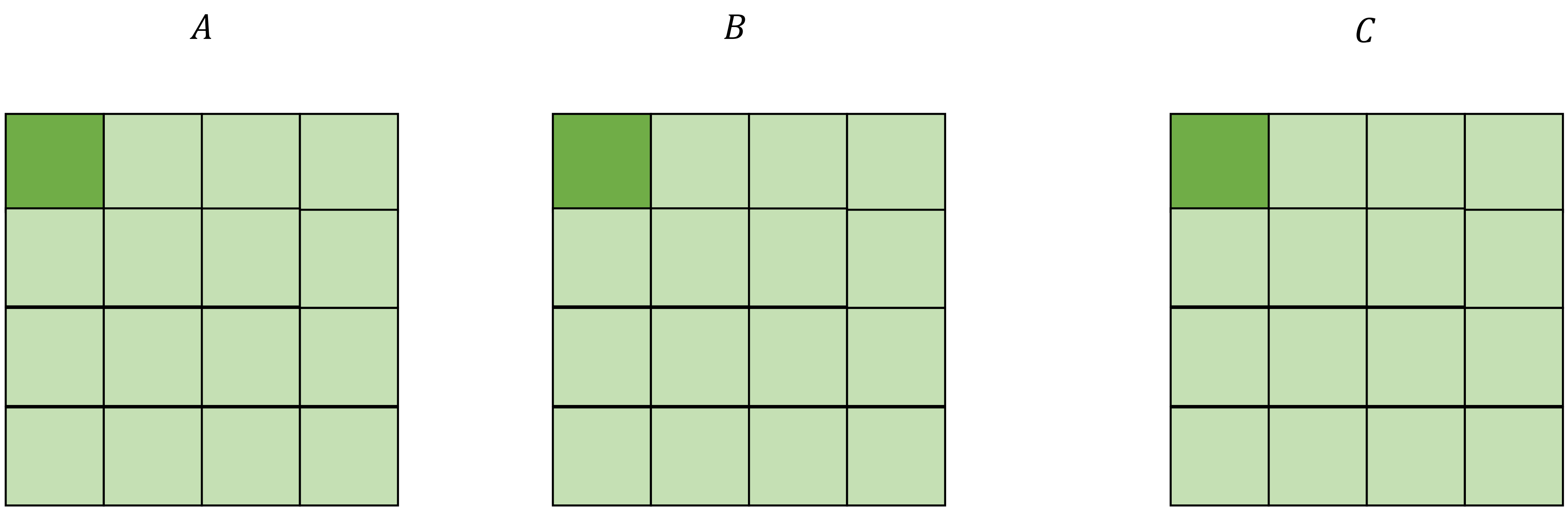
C



Adding loop nestings

- In some cases, there might not be a good nesting order for all accesses:

$$A = B + C^T$$

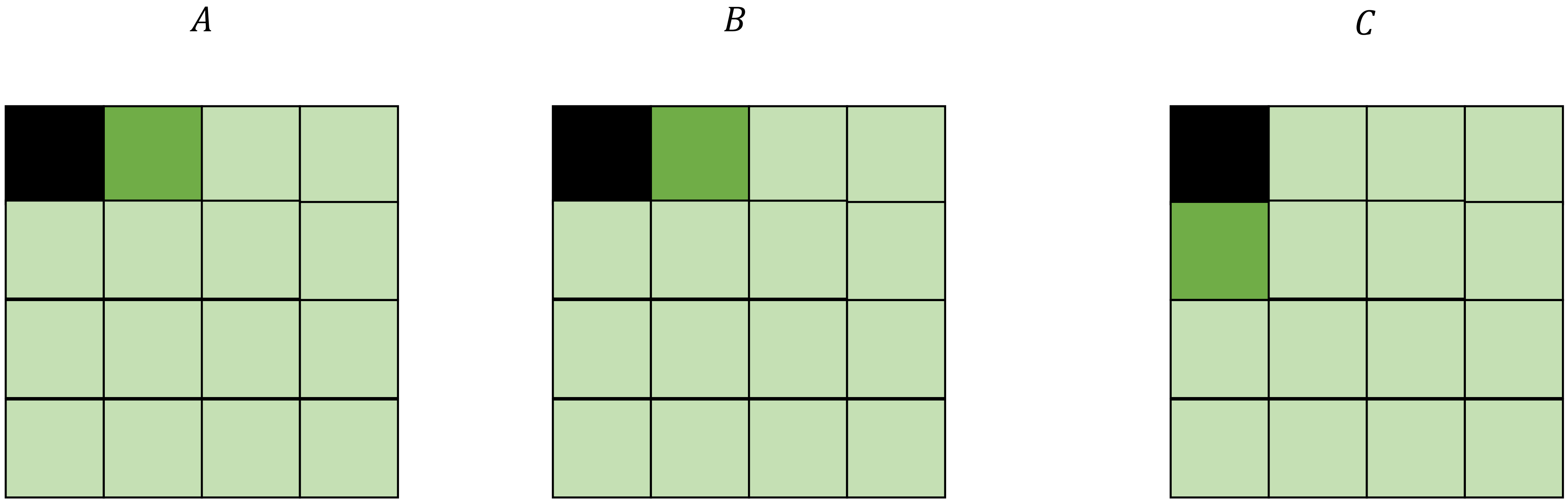


cold miss for all of them

Adding loop nestings

- In some cases, there might not be a good nesting order for all accesses:

$$A = B + C^T$$



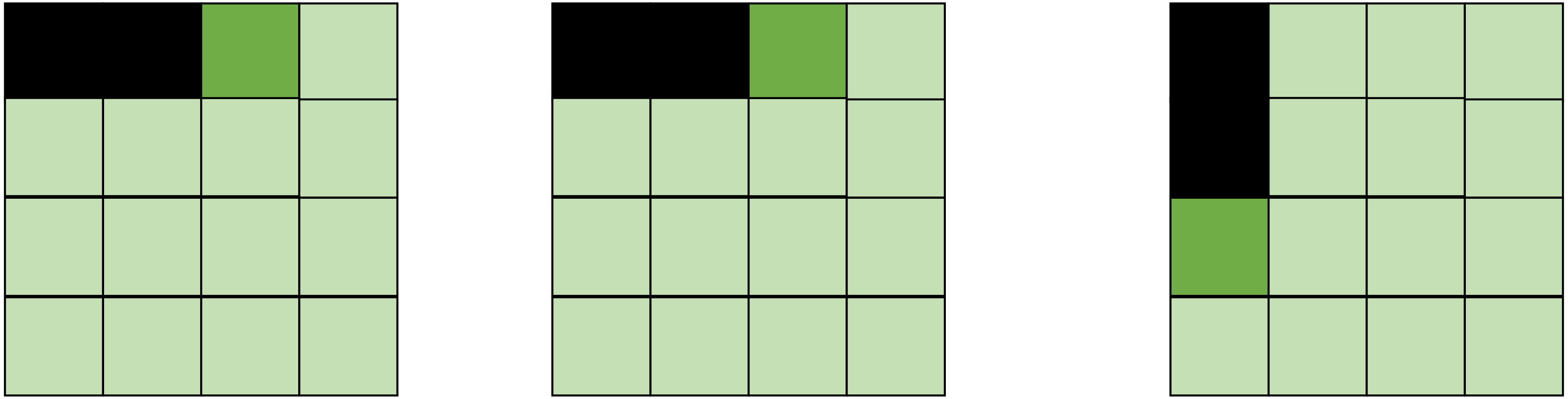
Hit on A and B. Miss on C

Adding loop nestings

- In some cases, there might not be a good nesting order for all accesses:

$$A = B + C^T$$

A $\qquad$ B $\qquad$ C



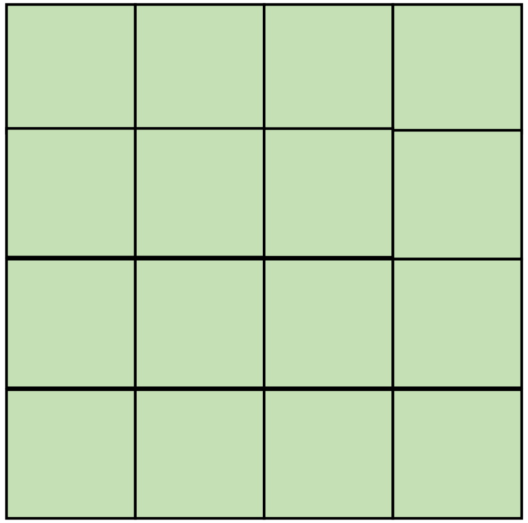
Hit on A and B. Miss on C

Adding loop nestings

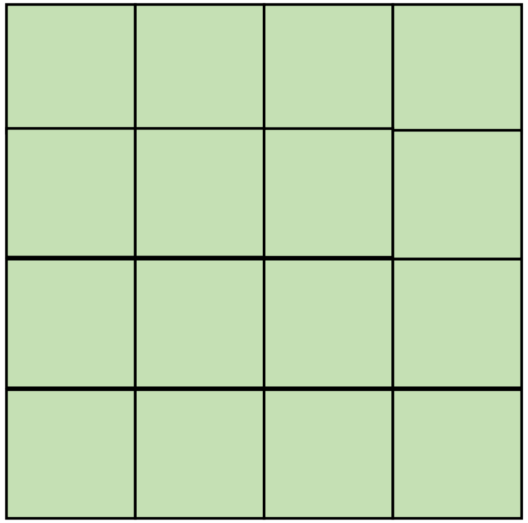
- Blocking operates on smaller chunks to exploit locality in column increment accesses. Example 2x2

$$A = B + C^T$$

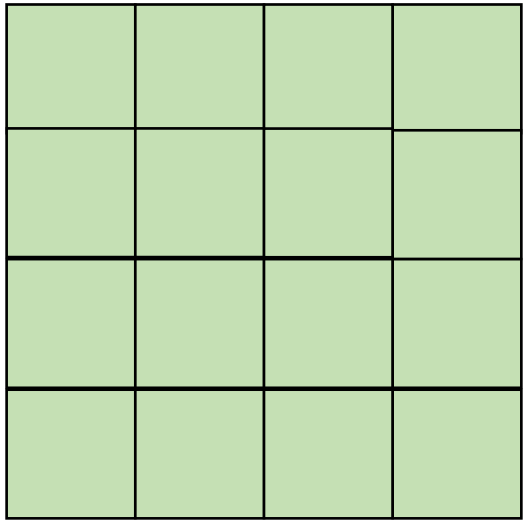
A



B



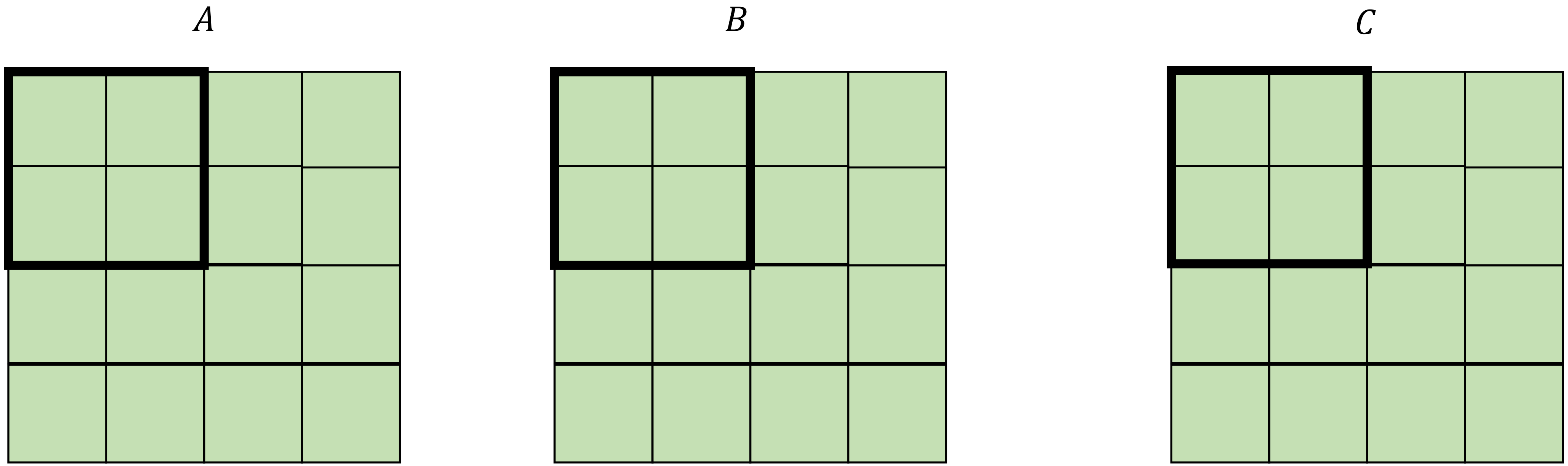
C



Adding loop nestings

- Blocking operates on smaller chunks to exploit locality in column increment accesses. Example 2x2

$$A = B + C^T$$

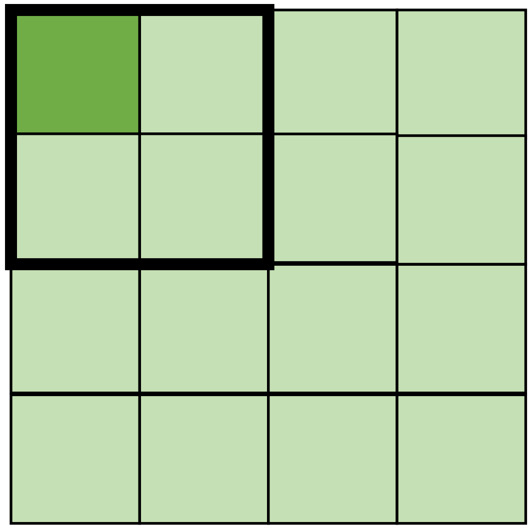


Adding loop nestings

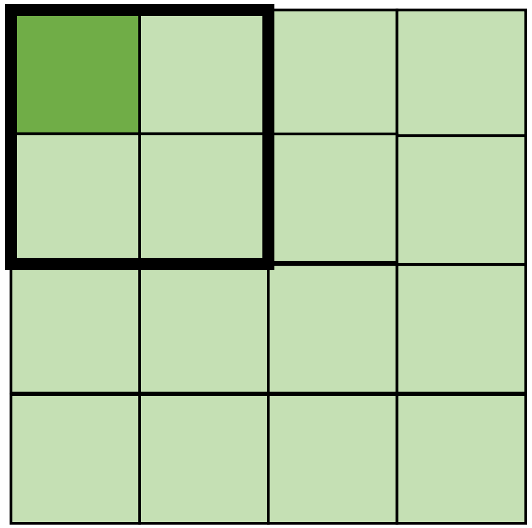
- Blocking operates on smaller chunks to exploit locality in column increment accesses. Example 2x2

$$A = B + C^T$$

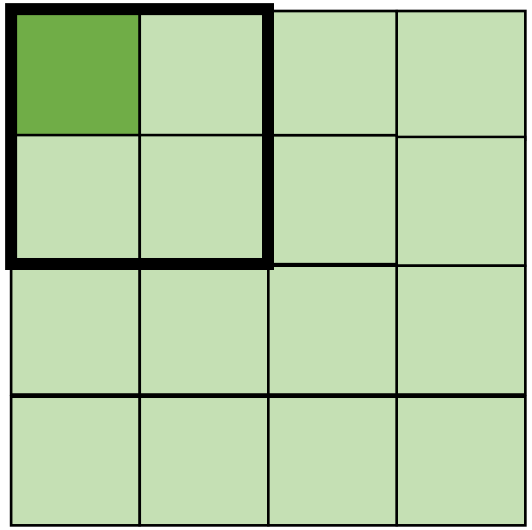
A



B



C

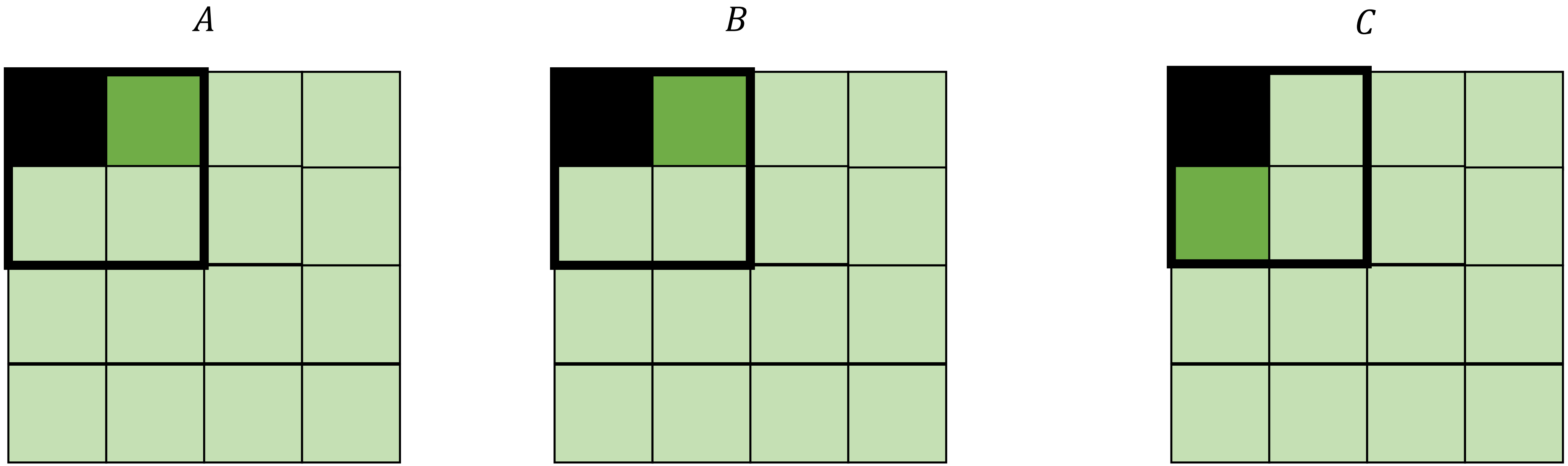


cold miss for all of them

Adding loop nestings

- Blocking operates on smaller chunks to exploit locality in column increment accesses. Example 2x2

$$A = B + C^T$$

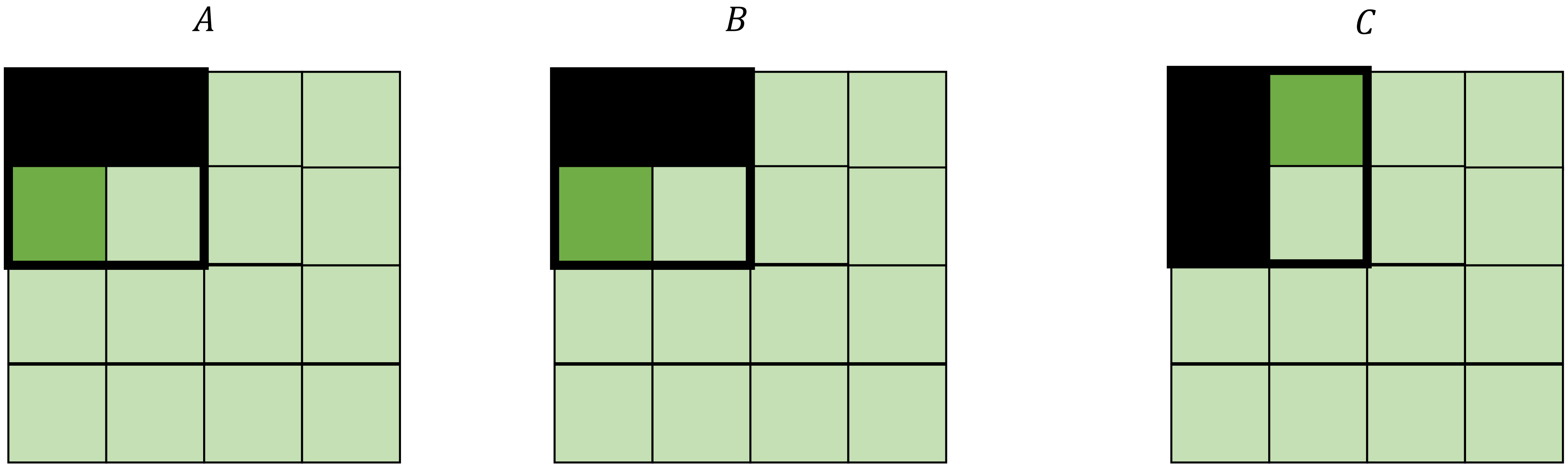


Miss on C

Adding loop nestings

- Blocking operates on smaller chunks to exploit locality in column increment accesses. Example 2x2

$$A = B + C^T$$

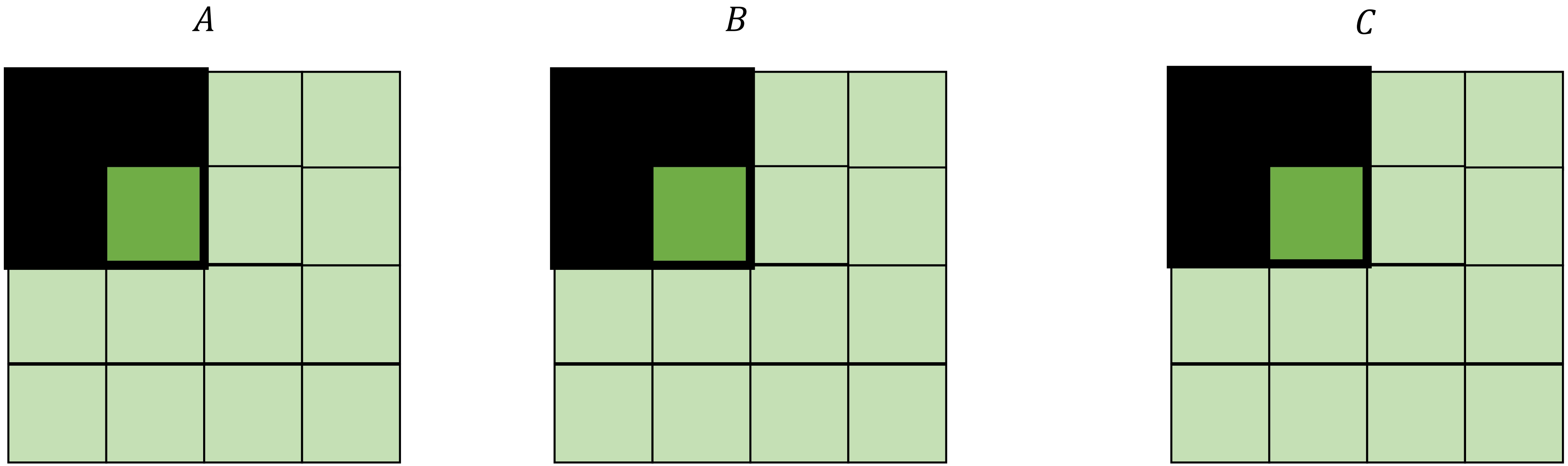


Miss on A,B, hit on C

Adding loop nestings

- Blocking operates on smaller chunks to exploit locality in column increment accesses. Example 2x2

$$A = B + C^T$$



Hit on all!

```
for (int x = 0; x < SIZE; x++) {
    for (int y = 0; y < SIZE; y++) {
      a[x*SIZE + y] = b[x*SIZE + y] + c[y*SIZE + x];
    }
  }
```

transforms into:

```
for (int xx = 0; xx < SIZE; xx += B) {
  for (int yy = 0; yy < SIZE; yy += B) {
    for (int x = xx; x < xx+B; x++) {
      for (int y = yy; y < yy+B; y++) {
        a[x*SIZE + y] = b[x*SIZE + y] + c[y*SIZE + x];
      }
    }
  }
}
```

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
                gradient.realize({16, 16});
```

Schedule

```
gradient.split(x, x_inner, x_outer, 4)
gradient.split(y, y_inner, y_outer, 4)
gradient.reorder(x_outer, y_outer, x_inner,
```

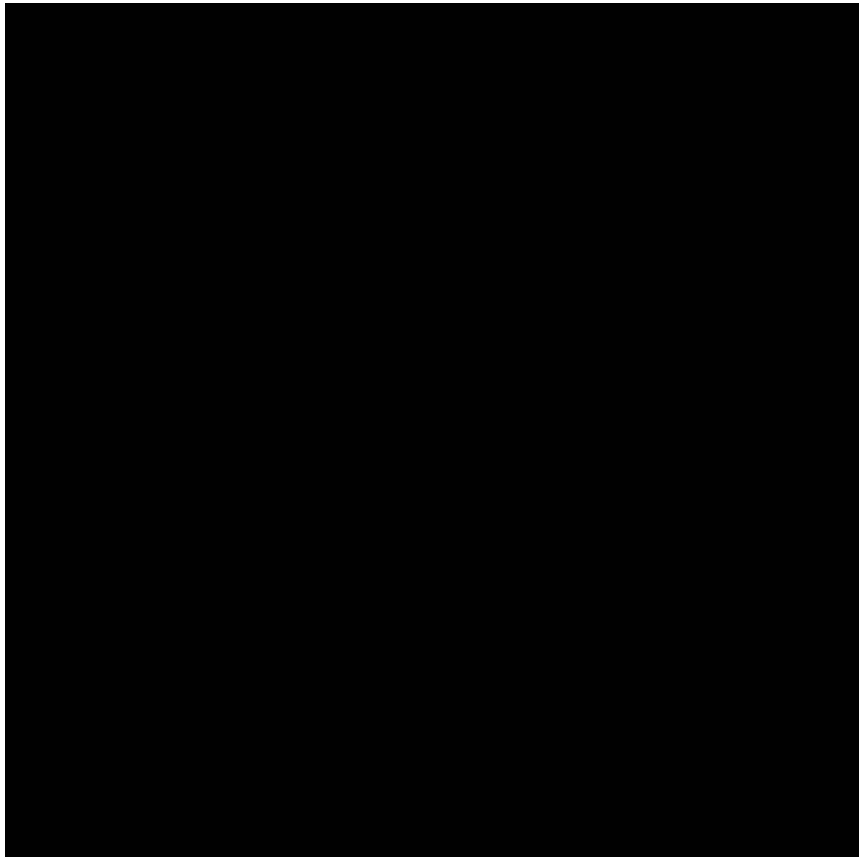
```
for (int y = 0; y < 16; y++) {
    for (int x = 0; x < 16; x++) {
        output[y,x] = x + y;
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({16, 16});
```

Schedule

```
Var x_outer, x_inner, y_outer, y_inner;
gradient.split(x, x_outer, x_inner, 4);
gradient.split(y, y_outer, y_inner, 4);
gradient.reorder(x_inner, y_inner, x_outer, y_outer);
```



```
for (int y = 0; y < 4; y++) {
    for (int x = 0; x < 4; x++) {
        output[y,x] = x + y;
    }
}
```

```
gradient.tile(x, y,
              x_outer, y_outer,
              x_inner, y_inner, 4, 4);
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({8, 4});
```

Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 2);
gradient.unroll(x_inner);
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
             gradient.realize({8, 4});
```

Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 2);
gradient.unroll(x_inner);
```

```
for (int y = 0; y < 4; y++) {
    for (int x_outer = 0; x_outer < 2; x_outer++) {
      {
          int x_inner = 0;
          int x = x_outer * 2 + x_inner;
          output(x,y) = x + y;
      }
      {
          int x_inner = 1;
          int x = x_outer * 2 + x_inner;
          output(x,y) = x + y;
      }
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

What about parallelism?

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({8, 4});
```

Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 4);
gradient.vectorize(x_inner);
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({8, 4});
```

Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 4);
gradient.vectorize(x_inner);
```

```
for (int y = 0; y < 4; y++) {
    for (int x_outer = 0; x_outer < 2; x_outer++) {

        int x_vec[] = {x_outer * 4 + 0,
                       x_outer * 4 + 1,
                       x_outer * 4 + 2,
                       x_outer * 4 + 3};

        int val[] =   {x_vec[0] + y,
                       x_vec[1] + y,
                       x_vec[2] + y,
                       x_vec[3] + y};
    }
}
```

from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({8, 4});
```

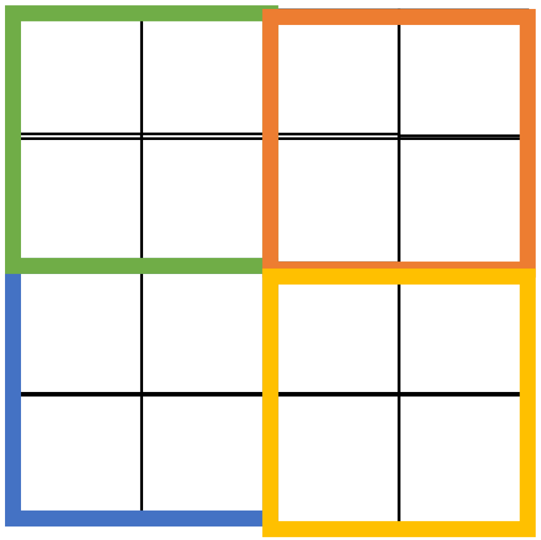
Schedule

```
Var x_outer, x_inner;
gradient.split(x, x_outer, x_inner, 4);
gradient.vectorize(x_inner);
```

```
for (int y = 0; y < 4; y++) {
    for (int x_outer = 0; x_outer < 2; x_outer++) {

        int x_vec[] = {x_outer * 4 + 0,
                       x_outer * 4 + 1,
                       x_outer * 4 + 2,
                       x_outer * 4 + 3};

        int val[] =   {x_vec[0] + y,
                       x_vec[1] + y,
                       x_vec[2] + y,
                       x_vec[3] + y};
    }
}
```

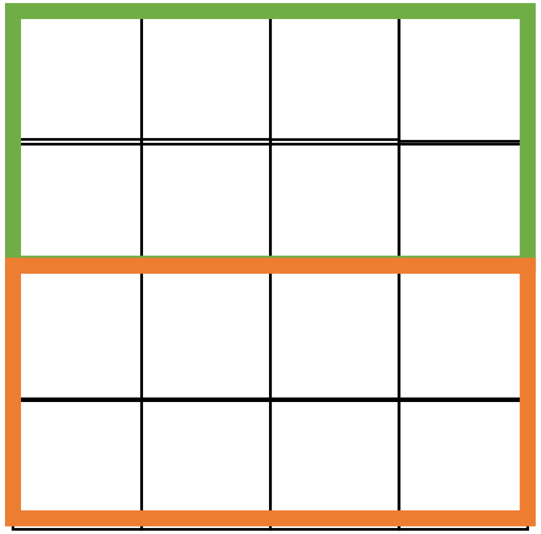
from: https://halide-lang.org/tutorials/tutorial_lesson_05_scheduling_1.html

```
for (int y_outer = 0; y_outer < 2; y_outer++) {
  for (int x_outer = 0; x_outer < 2; x_outer++) {
    for (int y_innder = 0; y_inner < 2; y_inner++) {
      for (int x_inner = 0; x_inner < 2; x_inner++) {
        ...
      }
    }
  }
}
```



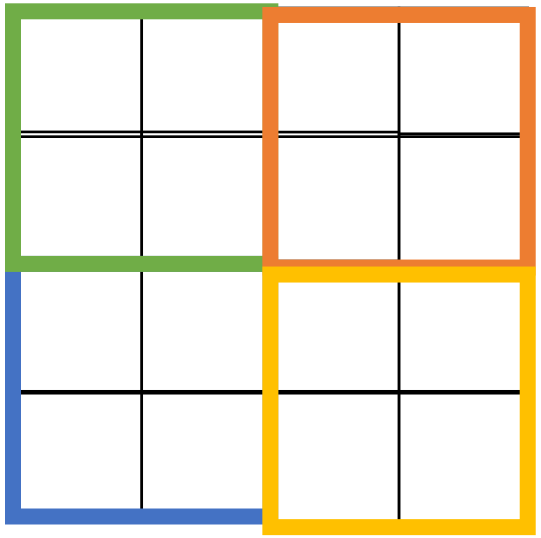
How can we make parallel across tiles?

```
for (int y_outer = 0; y_outer < 2; y_outer++) {
  for (int x_outer = 0; x_outer < 2; x_outer++) {
    for (int y_innder = 0; y_inner < 2; y_inner++) {
      for (int x_inner = 0; x_inner < 2; x_inner++) {
        ...
      }
    }
  }
}
```



if you make parallel across the outer loop

```
for (int fused = 0; fused < 4; fused++) {
    y_outer = fused/2;
    x_outer = fused%2;
    for (int y_innder = 0; y_inner < 2; y_inner++) {
      for (int x_inner = 0; x_inner < 2; x_inner++) {
        ...
      }
    }
  }
}
```



```cpp
Halide::Func gradient;
Halide::Var x, y;
gradient(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({2, 2});
```

Schedule

```cpp
Var x_outer, y_outer, x_inner,  y_inner, tile_index;

gradient.tile(x, y, x_outer, y_outer, x_inner, y_inner, 2, 2);

gradient.fuse(x_outer, y_outer, tile_index);

gradient.parallel(tile_index);
```

Finally: a fast schedule that they found:

```
Halide::Func gradient_fast;
Halide::Var x, y;
gradient_fast(x, y) = x + y;
Halide::Buffer<int32_t> output =
              gradient.realize({2, 2});



Var x_outer, y_outer, x_inner, y_inner, tile_index;
gradient_fast
              .tile(x, y, x_outer, y_outer, x_inner, y_inner, 64, 64)
              .fuse(x_outer, y_outer, tile_index)
              .parallel(tile_index);

Var x_inner_outer, y_inner_outer, x_vectors, y_pairs;
gradient_fast
       .tile(x_inner, y_inner, x_inner_outer, y_inner_outer, x_vectors, y_pairs, 4, 2)
       .vectorize(x_vectors)
       .unroll(y_pairs);
```

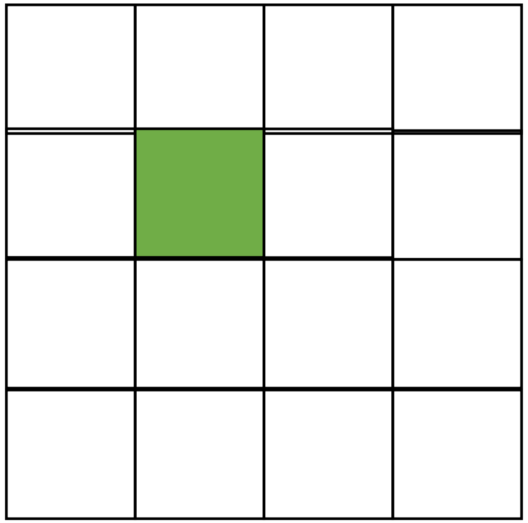
Now for function fusing...

Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

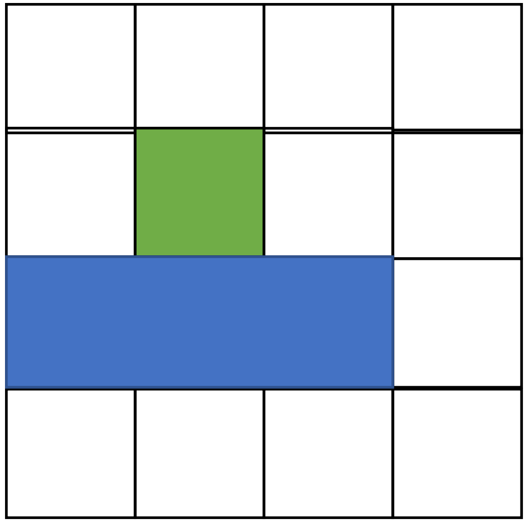
Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



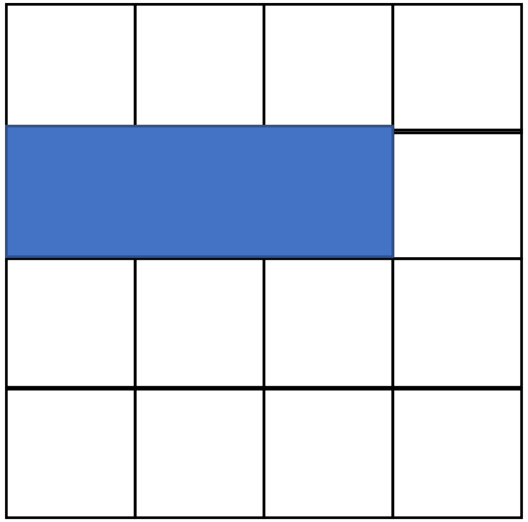
Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



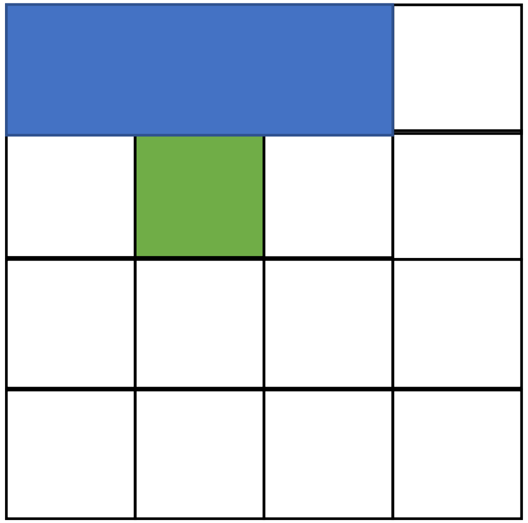
Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



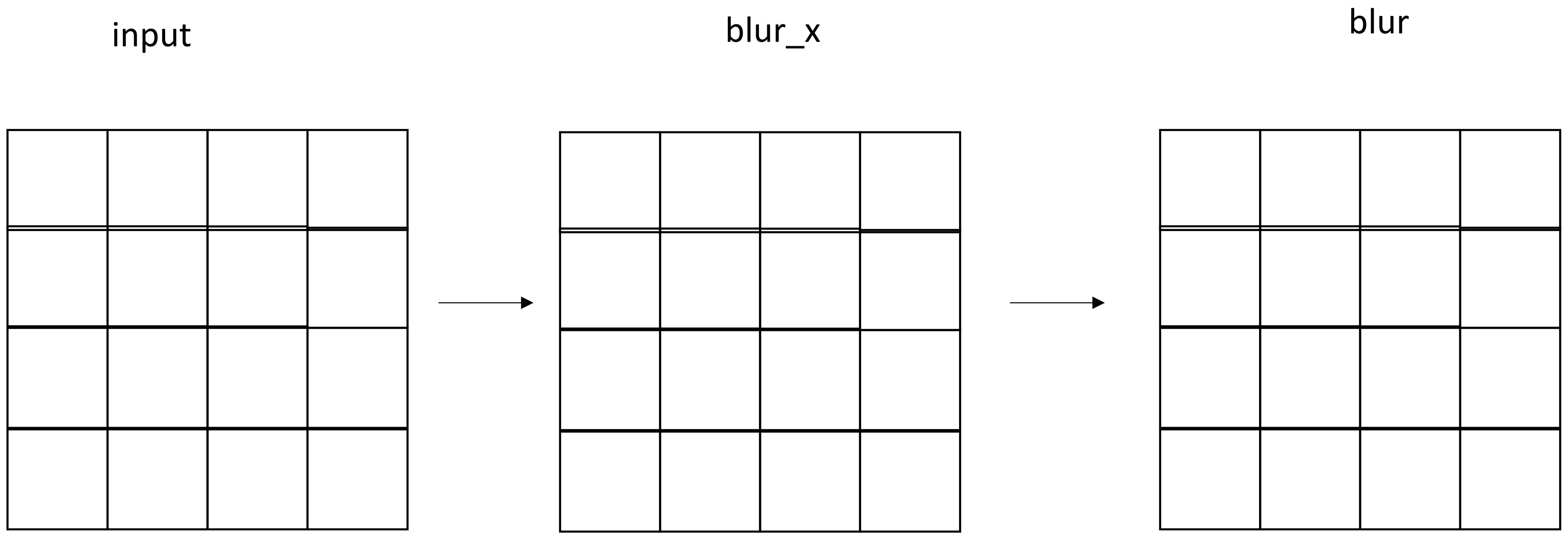
Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

how to compute?

Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

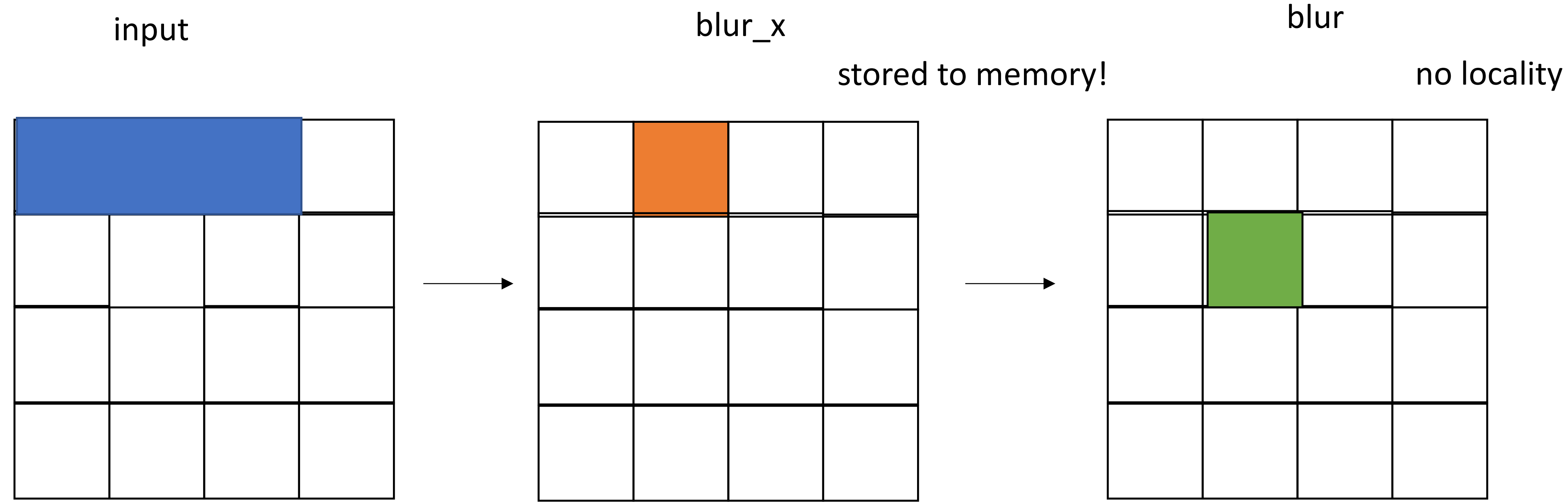
```
alloc blurx[2048][3072]
foreach y in 0..2048:
    foreach x in 0..3072:
      blurx[y][x] = in[y][x-1] + in[y][x] + in[y][x+1]
```

pros?
cons?

```
alloc out[2046][3072]
foreach y in 1..2047:
    foreach x in 0..3072:
      out[y][x] = blurx[y-1][x] + blurx[y][x] + blurx[y+1][x]
```

Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

Other options?

Example: unnormalized blur

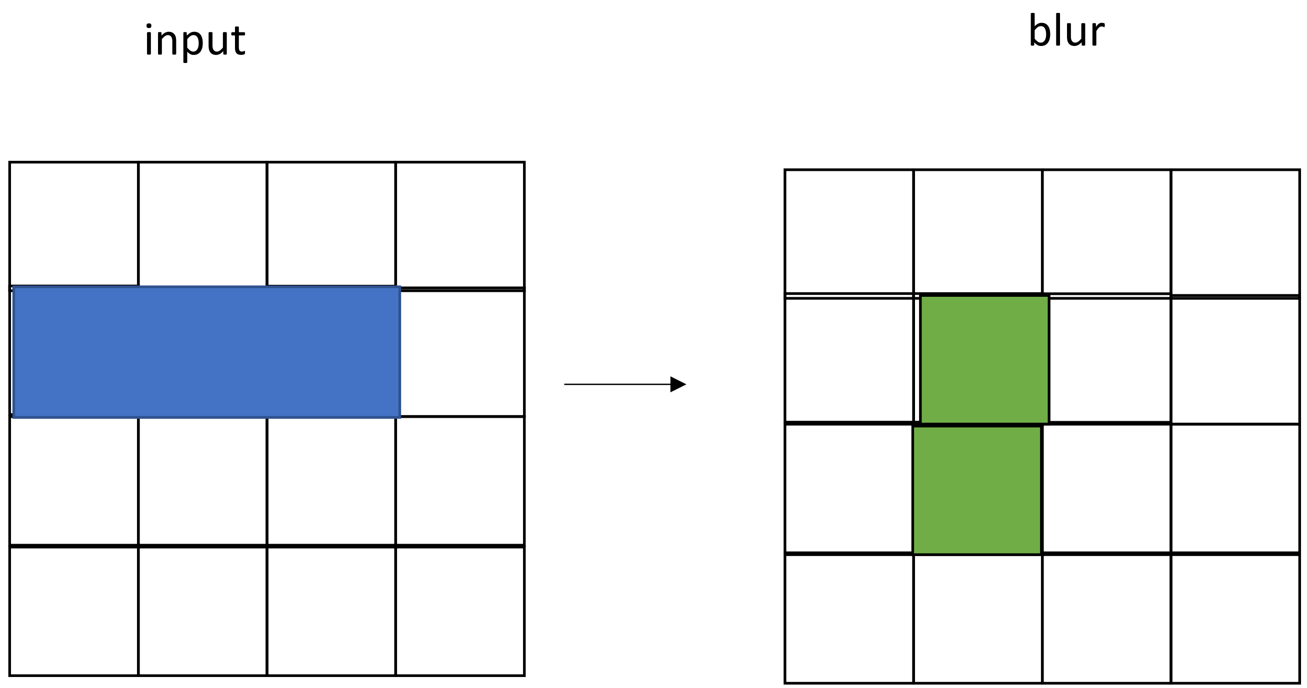
```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

completely inline

```
alloc out[2046][3072]
foreach y in 1..2047:
    foreach x in 0..3072:
      out[y][x] = in[y-1][x] + in[y][x] + in[y+1][x] +
                  in[y-1][x-1] + in[y][x-1] + in[y+1][x-1]
                  in[y-1][x+1] + in[y][x+1] + in[y+1][x+1]
```

Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```



These two squares will both sum up the same values in blue

Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

other ideas?

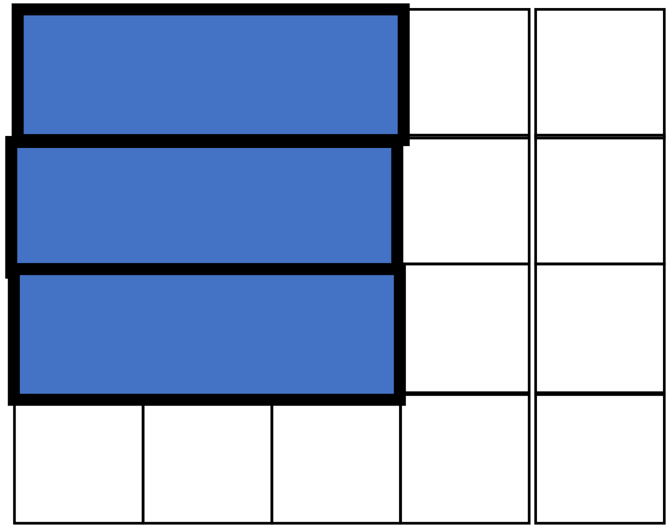
Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

first iteration, only compute blur_x

blur

sliding window



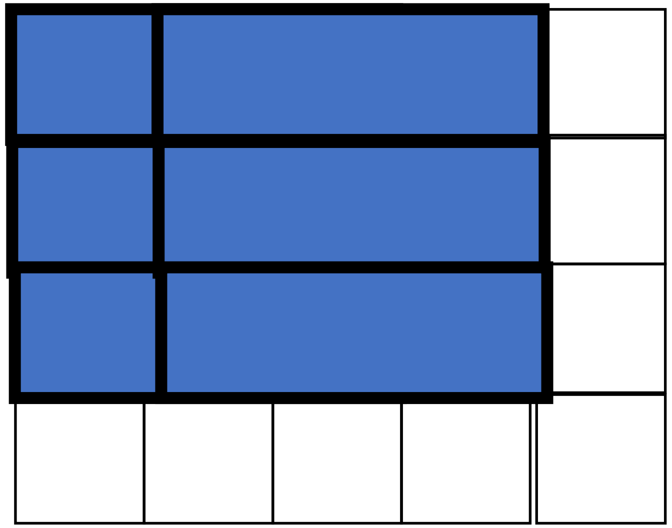
Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

first iteration, only compute blur_x
second iteration, compute blur_x again:

sliding window

blur

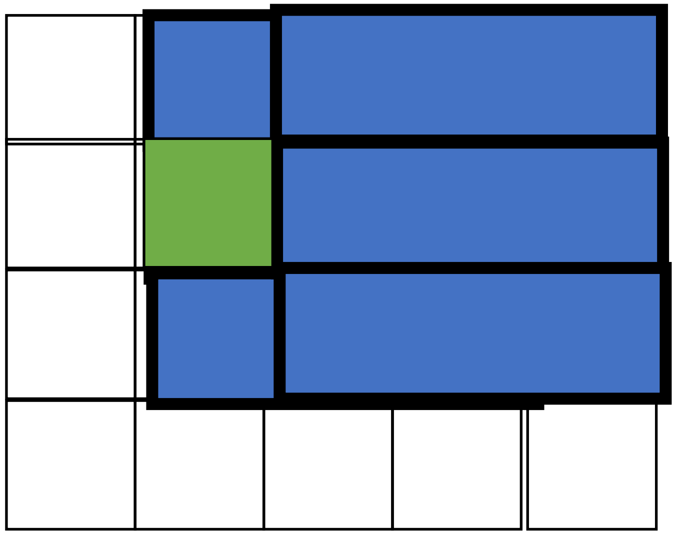


Example: unnormalized blur

```
Halide::Func blur_x(x,y) = in(x-1,y) + in(x,y) + in(x+1,y);

Halide::Func blur(x,y) = blur_x(x,y+1) + blur_x(x,y) + blur_x(x,y-1);
```

sliding window

blur



first iteration, only compute blur_x
second iteration, compute blur_x again:
third iteration, compute_blur_x again, but
also compute blur,

blur_x should be available,

pros? cons?

Pros cons of each?

- Completely different buffers?
- Completely inlined functions?
- Sliding window?

- Control through a “schedule” and search spaces.
- Fused functions can take advantage of all function schedules (e.g. tiling)