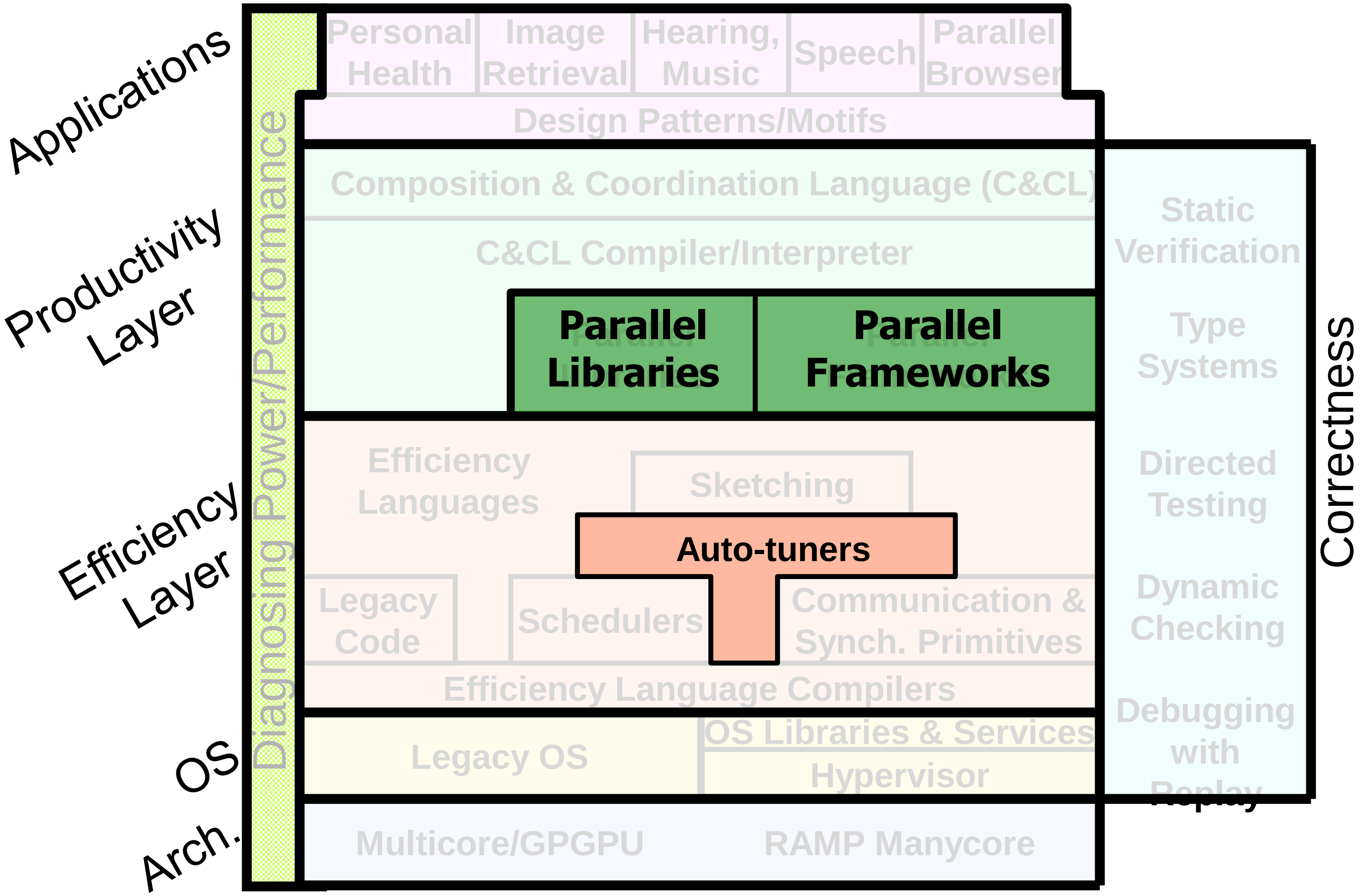
# Code Generators for Stencil Auto-tuning

Shoaib Kamil with Cy Chan, Sam Williams, Kaushik Datta, John Shalf, Katherine Yelick, Jim Demmel, Leonid Oliker

# Where this fits in Parlab



# Conventional Optimization

- Take one kernel/application
  - Perform some analysis
  - Research literature for appropriate optimizations
  - Implement some of them by hand-optimizing for one target machine
  - Iterate

- Result:

  Improve performance for **one** kernel on **one** computer

# Conventional Auto-tuning

- Automate the code generation and tuning process
  - Perform some analysis of the kernel
  - Research literature for appropriate optimizations
  - Implement a code generator and search mechanism
  - Explore optimization space

- Result:

  Improve performance for **one** kernel on **many** computers
  - Provides **performance portability**

- Downside:
  - Autotuner creation time is substantial
  - Must reinvent the wheel for every kernel

# Motif-specific Frameworks for Auto-tuning

- Programmers express calculation in high-level way
- Kernel represented internally in abstract form
- Auto-tuning system uses code transformation and generation to implement domain-specific transformations

- Result:

  Significantly improve performance for **many** kernels in a domain on **many** computers.
  - Obtain **performance portability without sacrificing productivity**

# Outline

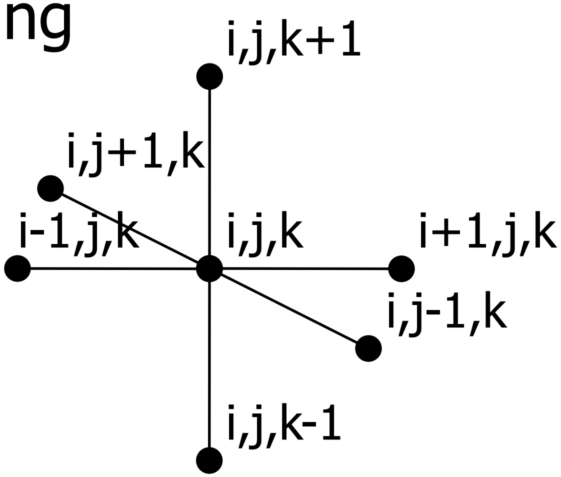
1. Stencils
2. Framework
3. Performance/Productivity Results
4. Stencils in High Level Dynamic Languages
5. Conclusions

# What's a stencil ?

- Nearest neighbor computations on structured grids (1D…ND array)

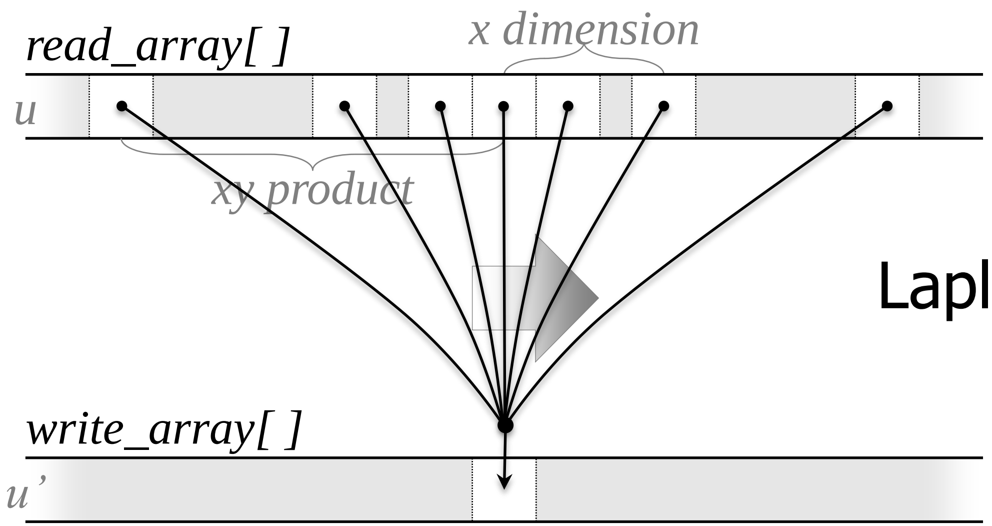
- Weights can be constant or vary depending on space, time, or data

- Used in applications such as PDE solvers, astrophysics,
climate simulation, image filtering



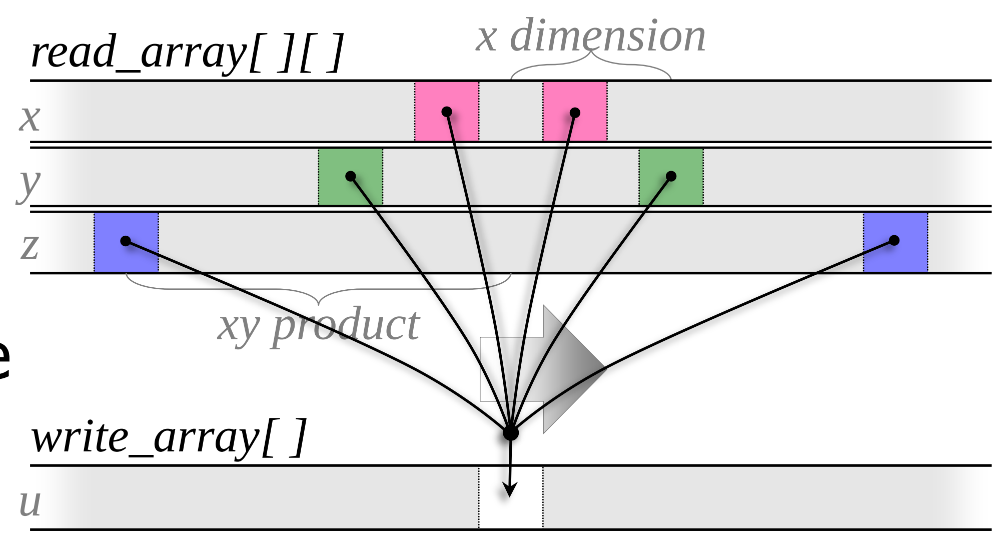

- Auto-tuning target: kernels with *separate read and write arrays*

# Studied Kernels




Laplacian

Divergence



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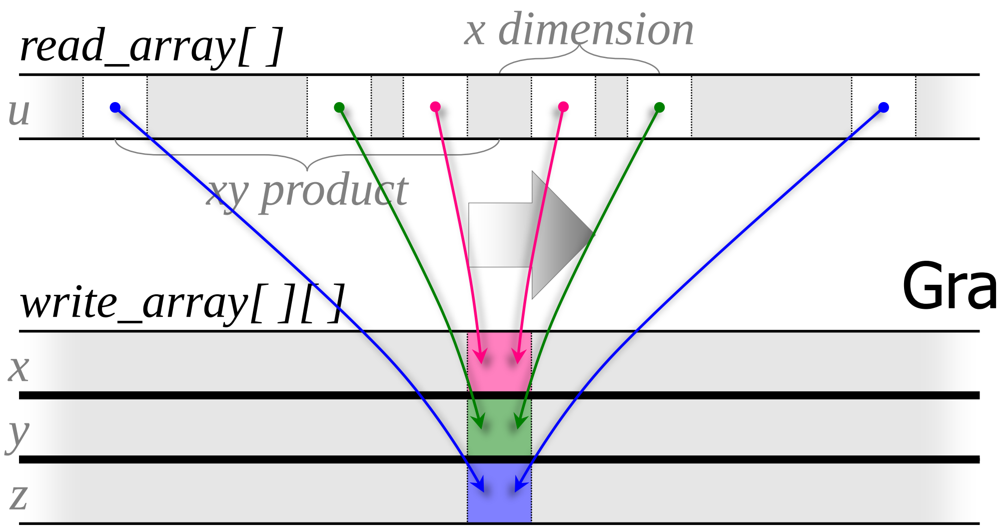
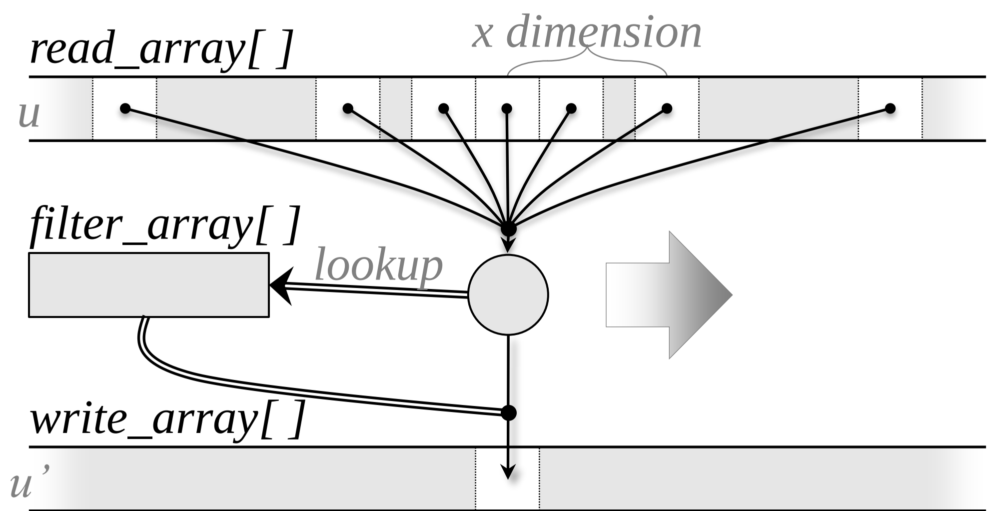



Gradient

Bilateral Filter



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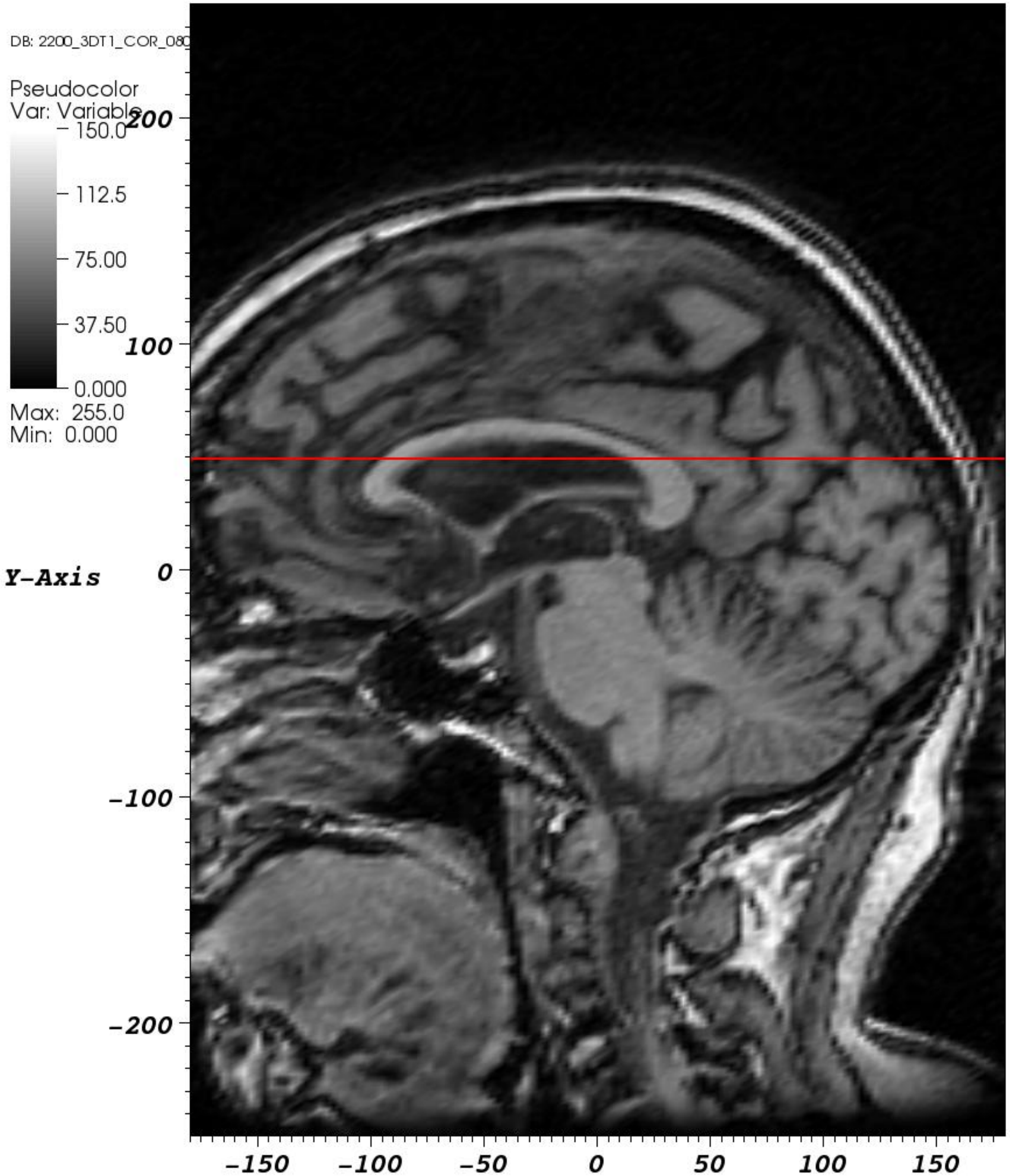

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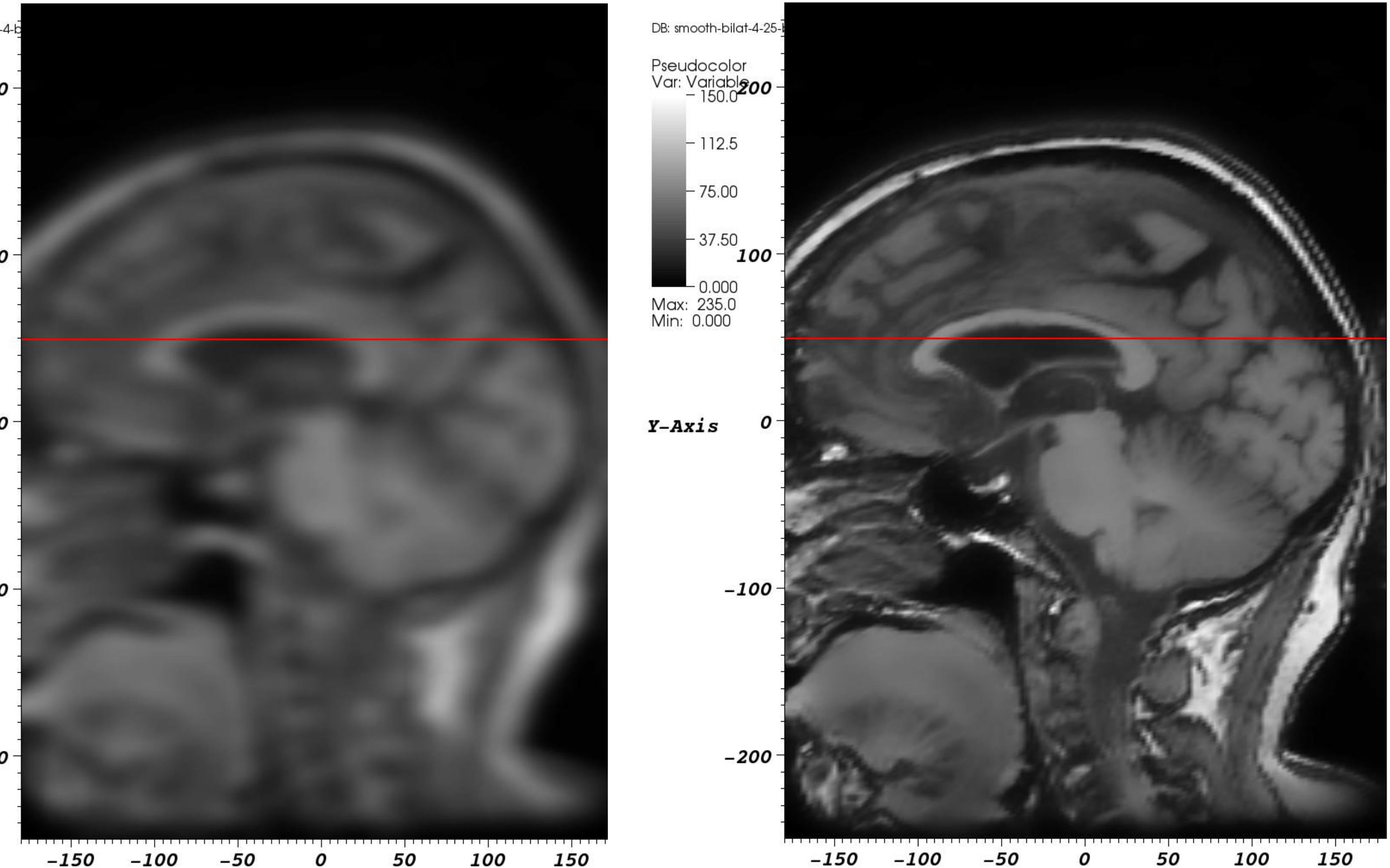

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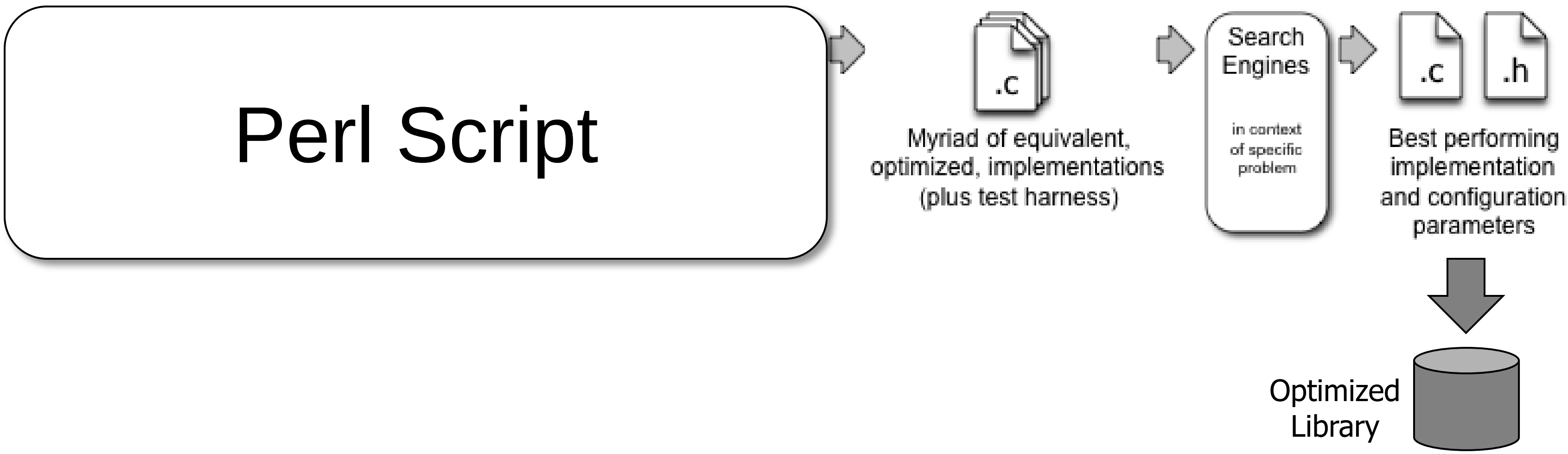
# Auto-tuner Overview



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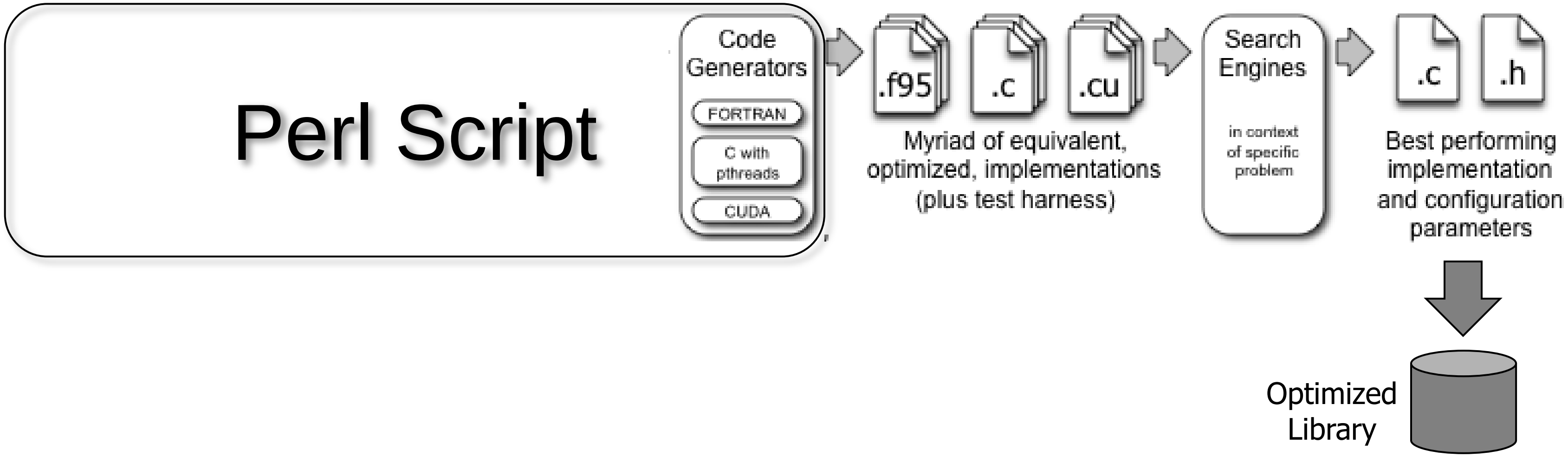

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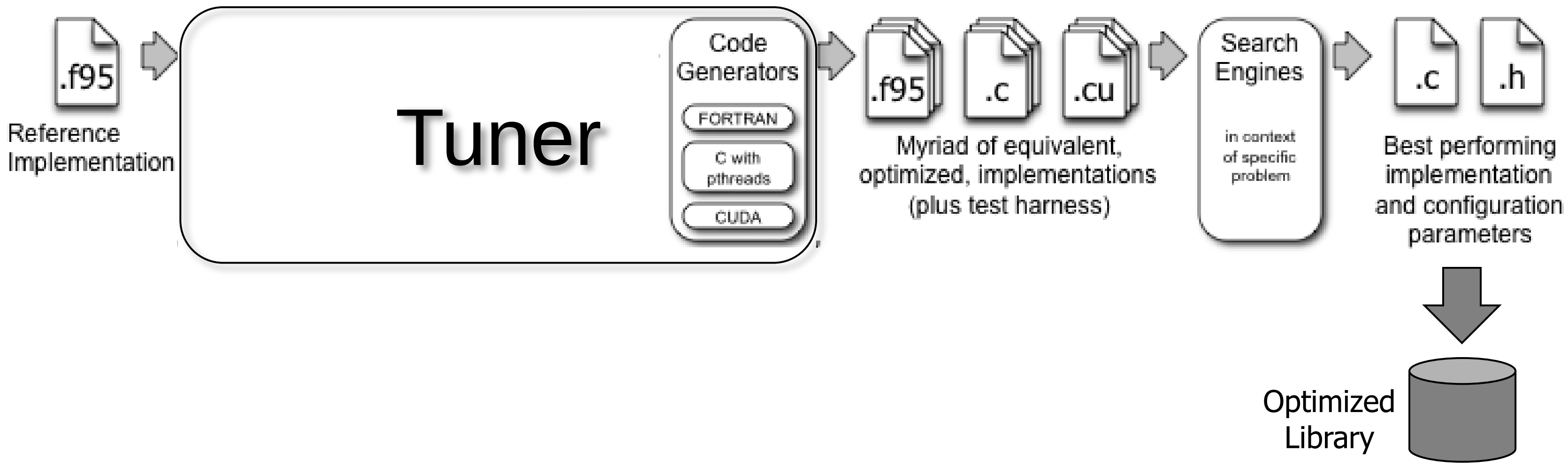

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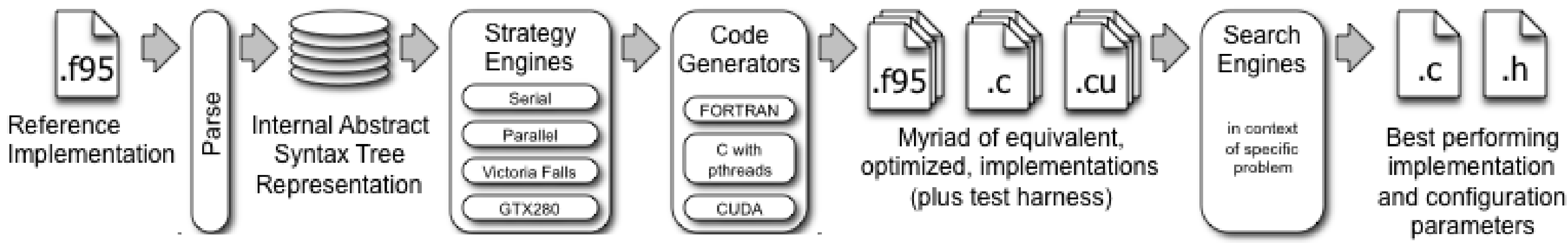
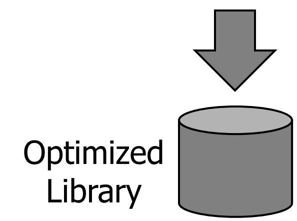



- Input is a high-level description/implementation of the kernel
- Framework parses into an internal representation
- Strategy Engines + Backend Code Generators optimize & generate candidate implementations
- End result: an optimized library containing best implementation

# Many-/Multi-core Strategy Engine

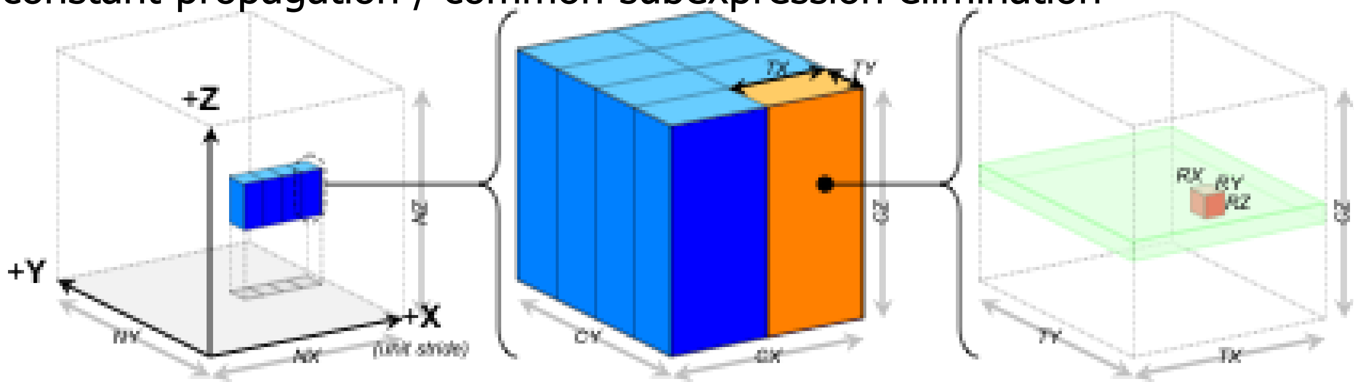
- Multicore strategy engine divides computation into cache blocks and distributes blocks over cores

- We use a single-program, multiple-data (SPMD) model implemented with POSIX Threads (Pthreads)
- All threads created at the beginning of the application

- Tuner produces initialization routine that exploits first-touch policy to ensure proper NUMA-aware allocation

# Many-/Multi-core Strategy Engine

- Strategy Engine explores a number of auto-tuning optimizations:
  - loop unrolling/register blocking
  - cache blocking
  - constant propagation / common subexpression elimination




(a) Decomposition of a Node Block into a Chunk of Core Blocks

(b) Decomposition into Thread Blocks

(c) Decomposition into Register Blocks

- Future Work:
  - cache bypass (e.g. *movntpd*)
  - software prefetching
  - SIMD intrinsics
  - data structure transformations

# CUDA Strategy Engine

- Strategy Engine parallelizes stencils using CUDA
- Exploit spatial locality by ensuring adjacent CUDA threads operate on adjacent memory locations
- Memory coalescing

- Auto-tuning
  - Explore shape of CUDA thread block
  - Like register blocking optimization in Multi-core

- Future Work:
  - Exploit temporal locality
    - Properly use memory in all levels of the hierarchy

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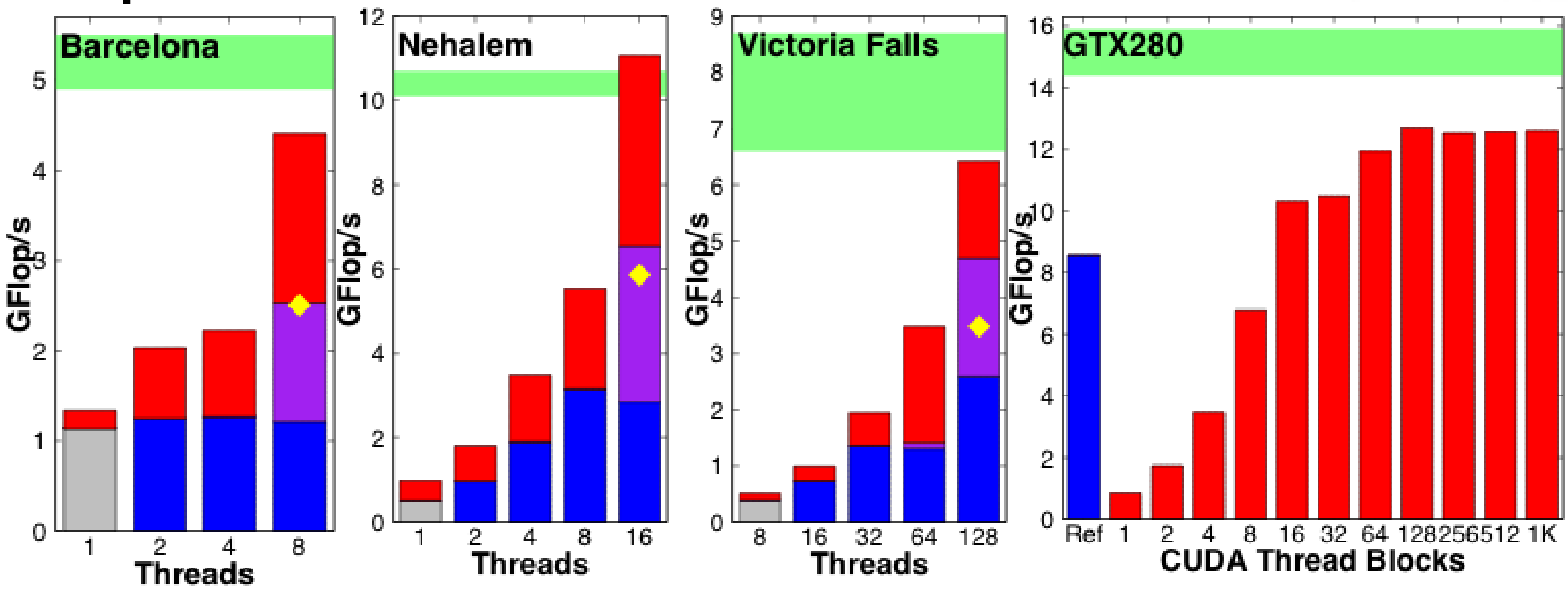
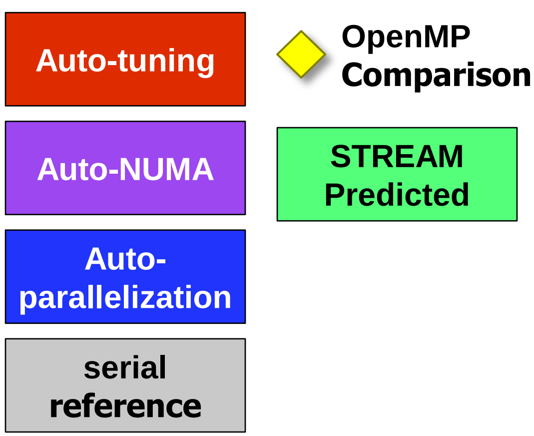
# Results Key

| | |
|---|---|
| serial reference | Original code in Fortran |
| Auto-parallelization | **Auto-parallelized** using the stencil framework (no tuning) |
| Auto-NUMA | Auto-parallelized **plus NUMA optimization** |
| Auto-tuning | **Auto-tuned** and auto-parallelized using the stencil framework |
| STREAM Predicted | Memory-bound **performance predicted using OpenMP STREAM** benchmark |
| OpenMP Comparison | Performance of a NUMA-aware auto-parallelized with **OpenMP version of the original code** |

# Laplacian Results

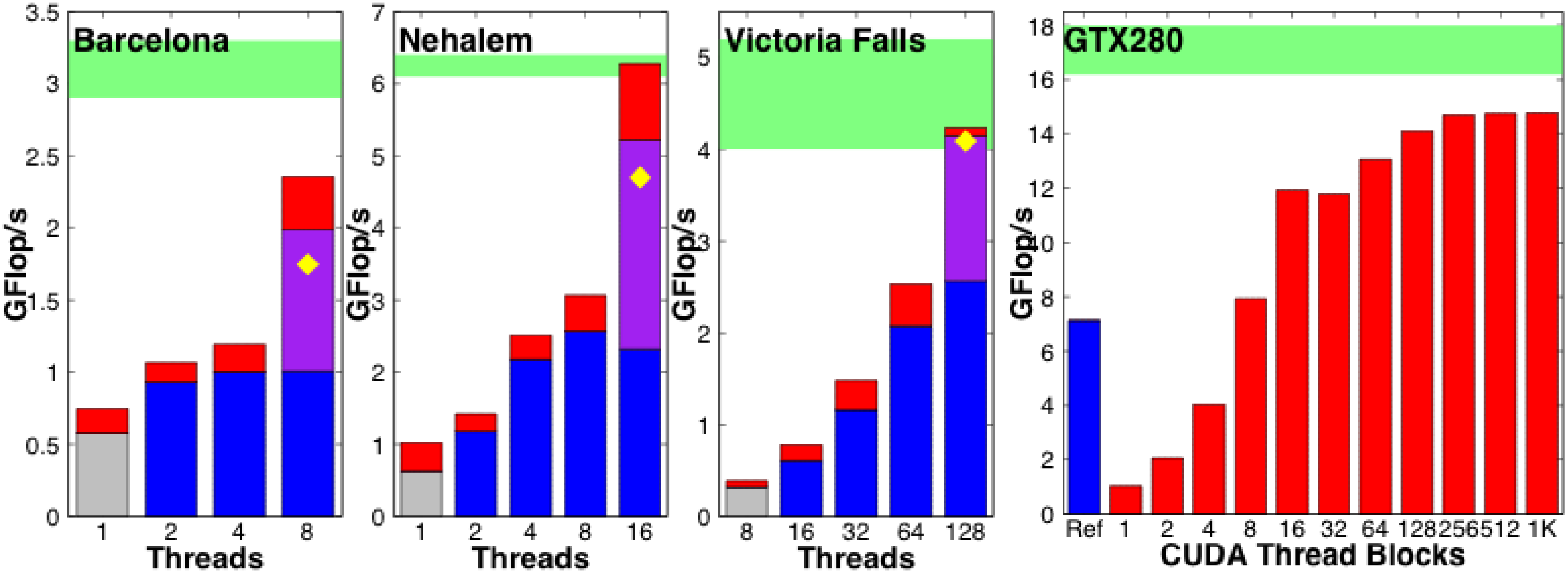



- Auto-parallelization by itself does not scale well on CPUs
  - requires NUMA-aware alloc to get decent performance
  - our auto-parallelizer gets equal or better performance than OpenMP

•Overall speedups of up to 22x on Nehalem (vs. serial reference), 1.5x on GTX280

# Divergence Results




Auto-tuning

OpenMP Comparison

Auto-NUMA

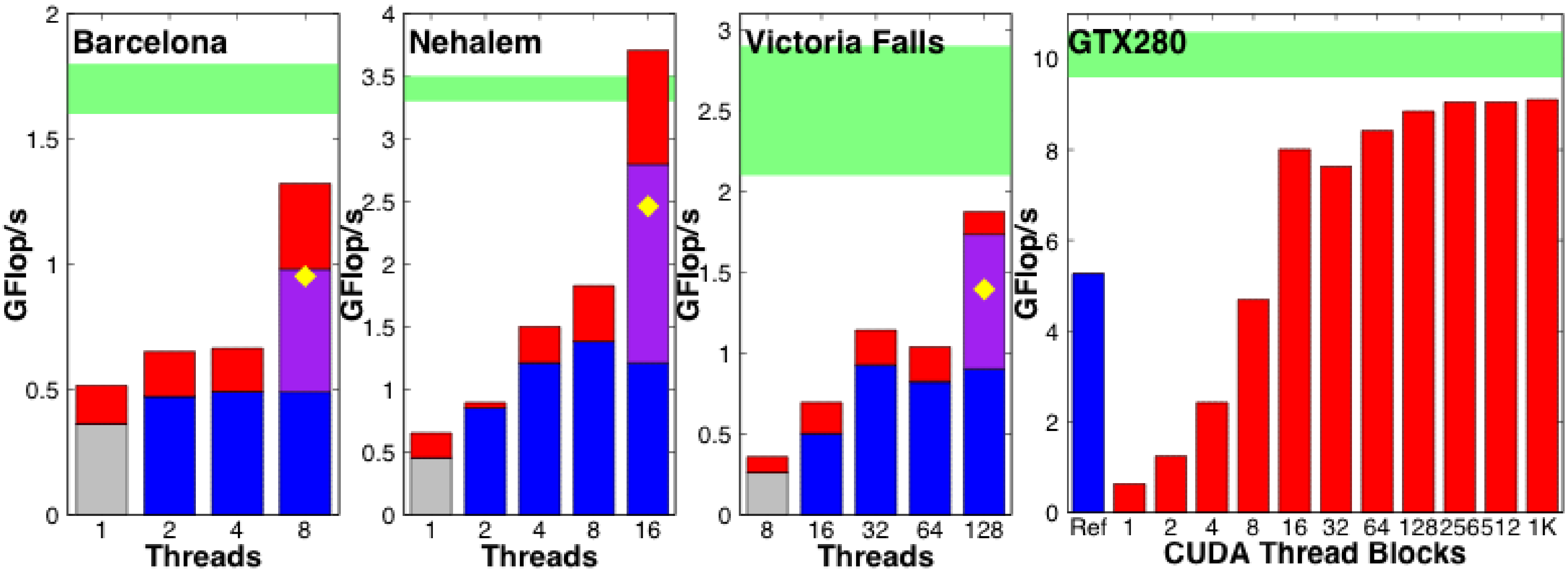
STREAM Predicted

Auto-parallelization

serial reference

- Less benefit from auto-tuning on cache-based architectures here
  - As we expect based on arithmetic intensity
- Overall speedups of up to 13x on Victoria Falls, 2x on GTX280

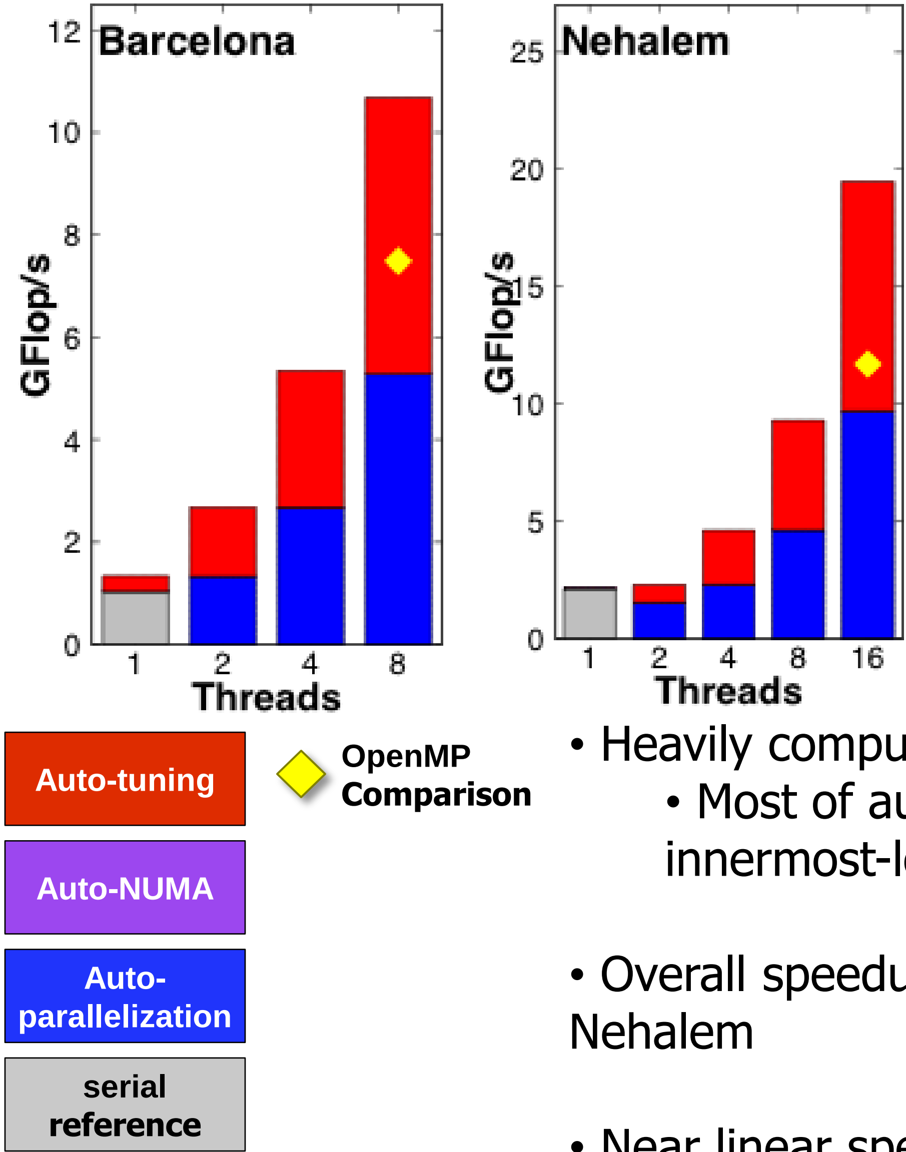
# Gradient Results




Auto-tuning
Auto-NUMA
Auto-parallelization
serial reference
OpenMP Comparison
STREAM Predicted

- Heavily memory-bound, so architectures with high memory BW get higher performance
- Overall speedups of up to 8.1x on Nehalem, 1.7x on GTX280

# Bilateral Filter Results (r=3)




- Heavily compute-bound, plus lookup for filter weights
    - Most of auto-tuning benefit comes from better innermost-loop
- Overall speedups of 14.8x for Barcelona, 20.7x for Nehalem
- Near linear speedup as cores increase

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# High Level Languages

Common complaint from domain scientists: too much overhead in experimenting with kernels
  - Must manage memory, array layouts, etc

- Languages like Ruby & Python support high-level programming with frameworks & libraries

- What would productive *parallel* stencil support look like in Ruby?
  - Must deal with lack of thread-safety in interpreter

# One Approach

- Solution: write stencil in Ruby
  - Use conventions to simplify code structure

Then, **transparently**:

- Use Ruby’s introspective nature to parse code
- Dynamically translate to C, compile, link, and execute translated code on Ruby data structure

- Only translate the stencil kernel: the rest is still in pure Ruby

# Example

```
class LaplacianKernel < JacobiKernel
def kernel(in_grid, out_grid)
    in_grid.each_interior do |center|
      in_grid.neighbors(center,1).each do |x|
        out_grid[center] = out_grid[center]
          + 0.2 * in_grid[x]
      end
    end
  end
end
```

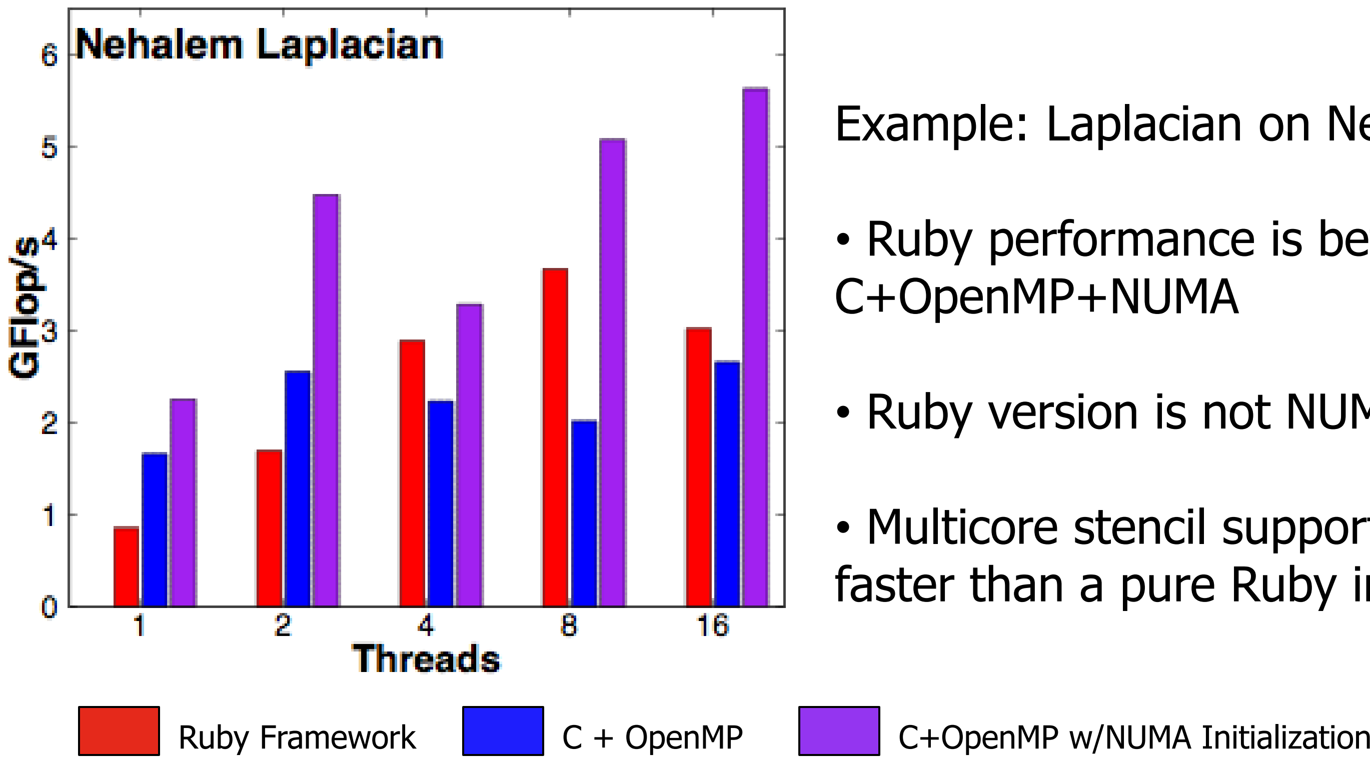
When the Ruby program calls kernel() this is automatically generated, compiled, and run

```
VALUE kern_par(int argc, VALUE* argv, VALUE self) {
struct NARRAY *temp_4;
double* in_grid;
GetNArray(argv[0], temp_4);
in_grid = (double*) NA_PTR(temp_4, 0);
struct NARRAY *temp_5;
double*  out_grid;
GetNArray(argv[1], temp_5);
out_grid = (double*) NA_PTR(temp_5, 0);
int temp_8;
int temp_7;
int temp_6;

#pragma omp parallel for default(shared)  private
(temp_6,temp_7,temp_8)
for (temp_8=1; temp_8<256-1; temp_8++) {
for (temp_7=1; temp_7<256-1; temp_7++) {
for (temp_6=1; temp_6<256-1; temp_6++) {
int center = INDEX(temp_6,temp_7,temp_8);
out_grid[center] = (out_grid[center]
    +(0.2*in_grid[INDEX(temp_6-1,temp_7,temp_8)]));
out_grid[center] = (out_grid[center]
    +(0.2*in_grid[INDEX(temp_6+1,temp_7,temp_8)]));
out_grid[center] = (out_grid[center]
    +(0.2*in_grid[INDEX(temp_6,temp_7-1,temp_8)]));
out_grid[center] = (out_grid[center]
    +(0.2*in_grid[INDEX(temp_6,temp_7+1,temp_8)]));
out_grid[center] = (out_grid[center]
    +(0.2*in_grid[INDEX(temp_6,temp_7,temp_8-1)]));
out_grid[center] = (out_grid[center]
    +(0.2*in_grid[INDEX(temp_6,temp_7,temp_8+1)]));
;}}}
return Qtrue;}
```

# Results

- Comparable performance to OpenMP+C
- First execution takes more time (JITing)
  - Subsequent executions are fast




Example: Laplacian on Nehalem (25 iterations)

• Ruby performance is between C+OpenMP and C+OpenMP+NUMA

• Ruby version is not NUMA-aware

• Multicore stencil support in Ruby is >500x faster than a pure Ruby implementation

# Summary

- Summer 2008 Retreat: feedback that auto-tuners are not very auto
- Winter 2008 Retreat: Presented idea of auto-tuners for a class of kernels
  - Serial results for 1 kernel
- Now: Parallel stencil auto-tuning for many kernels on many architectures
- Obtain performance and platform portability
- High level dynamic languages can use same techniques to produce portable efficient code
- Lots of future work: better CUDA/OpenCL support, widen class of supported stencils

# Acknowledgements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