# Recent Results, Insights and Lessons from Autotuning Three Motifs

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# Overview



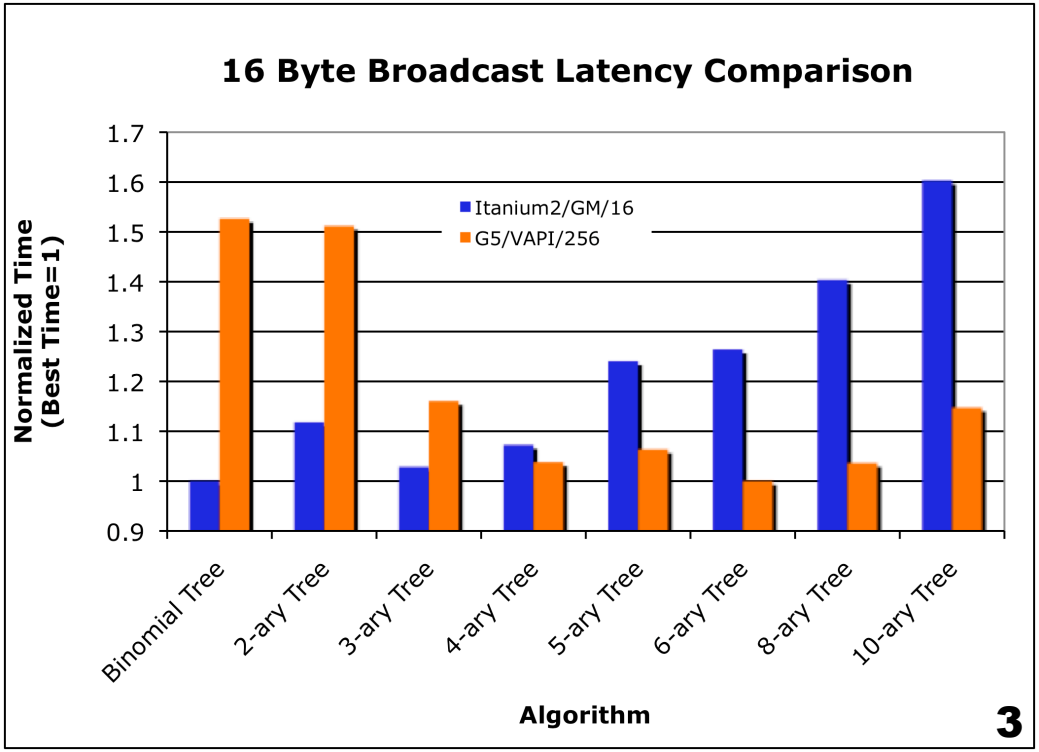
- Other autotuning at Berkeley
- Recent work autotuning three parallel kernels
  - Sparse Matrix Vector Multiply (SpMV)
  - Lattice Boltzmann MHD
  - Stencils (Heat Equation)
- Integrating SpMV Advances into OSKI
- Towards a framework for building autotuners
  - What is the role of the compiler?
- Open questions

# Other Autotuning Work



- Using Delta Debugging to automatically "fix" precision errors
  - attempt to use extra precision only when necessary
  - preliminary implementation by Kamil with Kaushik Sen

- Autotuning PGAS Collectives
  - Using run-time and install-time tuning to speed up collective operations such as barrier, reductions, etc.
  - Tuning space involves trees for collective operations
  - Current work by Rajesh Nishtala



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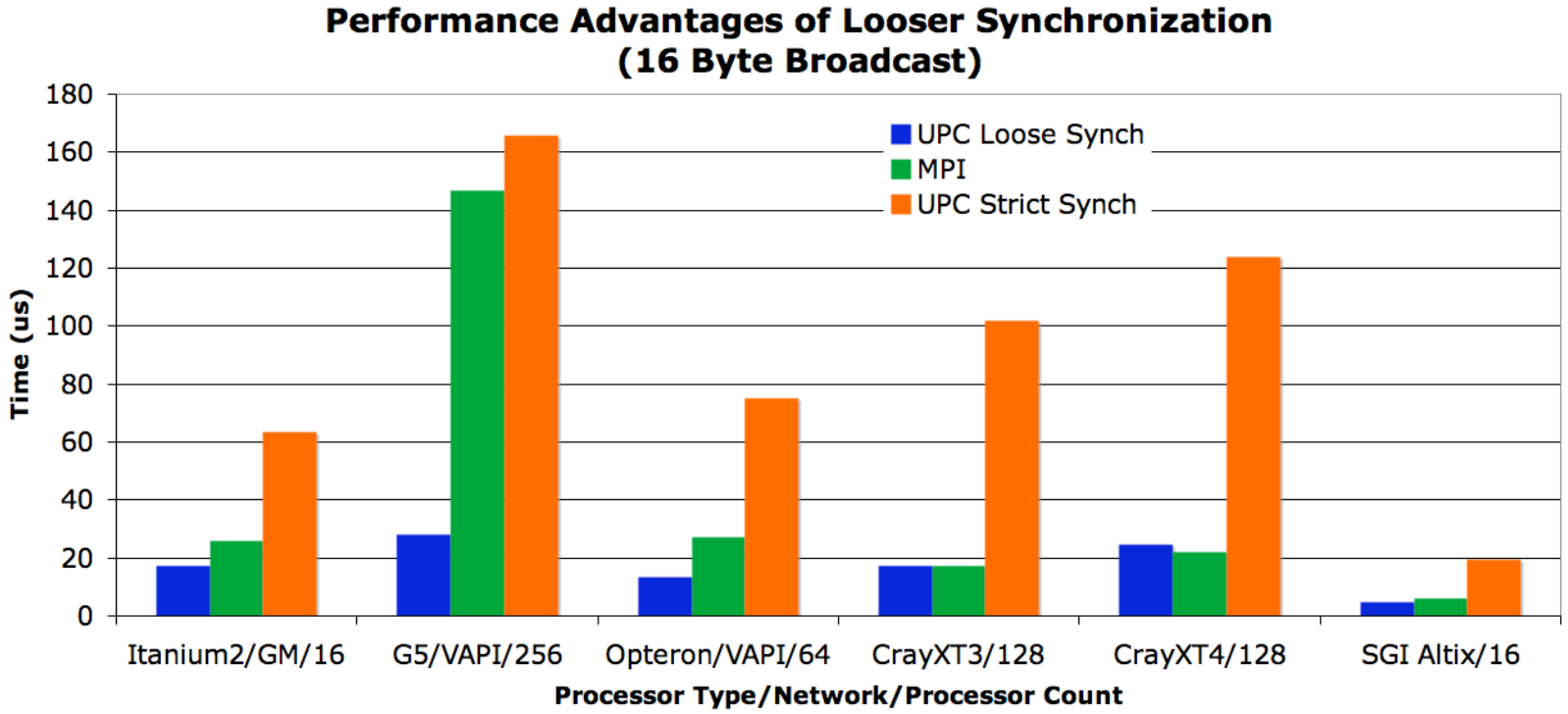
- Autotuning PGAS Collectives



# SpMV, Stencil, LBMHD



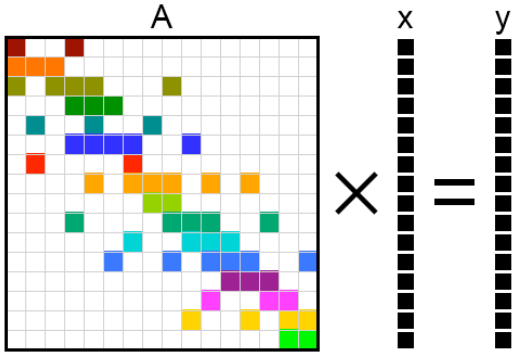
- Recent autotuning results from these kernels

| | Regular Entries | Irregular Entries |
|---|---|---|
| **Regular Sparsity Pattern** | Stencil, LBMHD, Climate | Image Segmentation |
| **Irregular Sparsity Pattern** | Laplacian of a Graph | SpMV |

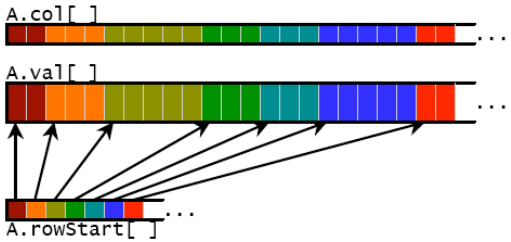
# SpMV Overview



- A *sparse* matrix has few non-zeros
  - Performance advantage in only storing/operating on non-zeros
  - Requires significant metadata
- Our sparse matrix-vector multiply (**Ax** = **y**) operation represents:
  - **A** as a sparse matrix in Compressed Sparse Row (CSR) format
  - **x** and **y** as dense contiguous vectors
- SpMV has indirect and irregular memory access patterns




**(a)**
algebra conceptualization




**(b)**
CSR data structure

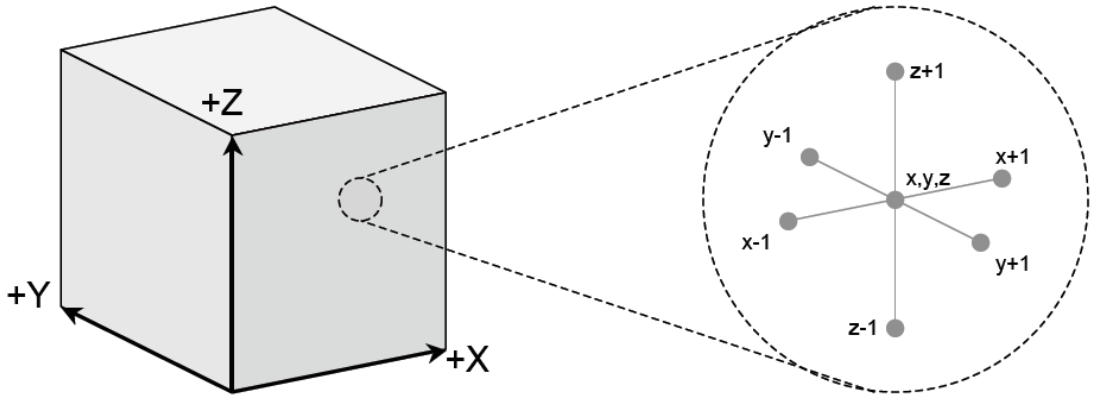
```
for (r=0; r<A.rows; r++) {
  double y0 = 0.0;
  for (i=A.rowStart[r]; i<A.rowStart[r+1]; i++){
    y0 += A.val[i] * x[A.col[i]];
  }
  y[r] = y0;
}
```

**(c)**
CSR reference code

# Heat Equation Stencil Overview



- A *stencil code* updates every point in a regular grid with a constant weighted subset of its neighbors
- Typically derive from finite-difference techniques for solving PDE's
- Stencils have direct and regular memory access patterns
- We examine an out-of-place 3D 7-point stencil with constant coefficients




**(a)**
PDE grid

**(b)**
stencil for heat equation PDE

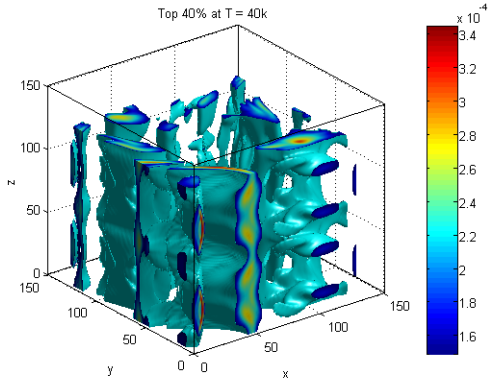
```
Next[x,y,z] =
    C0 * Current[x,y,z] +
    C1 *(
         Current[x+1,y,z] +
         Current[x-1,y,z] +
         Current[x,y+1,z] +
         Current[x,y-1,z] +
         Current[x,y,z+1] +
         Current[x,y,z-1]
        );
```

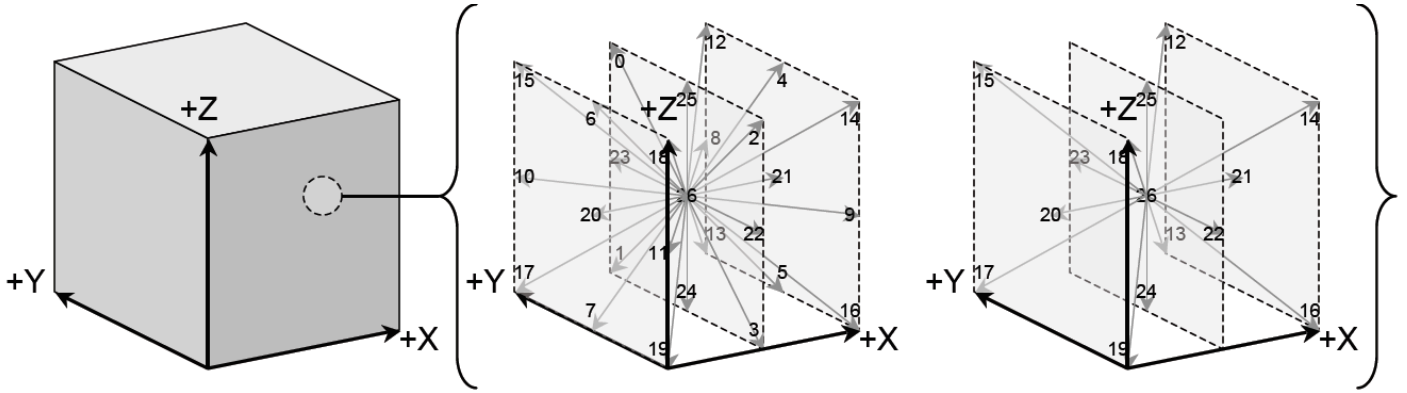
**(c)**
inner loop

# LBMHD Overview
## (Lattice Boltzmann Magneto-Hydrodynamics)



- Plasma turbulence simulation (structured grid code with time steps)
- Two distributions:
  - Momentum distribution (27 scalar velocities)
  - Magnetic distribution (15 vector velocities)
- Three macroscopic quantities:
  - Density
  - Momentum (vector)
  - Magnetic field (vector)
- Distribution functions used to reconstruct macroscopic quantities
- For each spatial point in $128^3$ grid:
  - 73 doubles read and 79 doubles written (min 1200 bytes)
  - Approximately 1300 flops performed




(a) macroscopic variables

(b) momentum distribution

(c) magnetic distribution

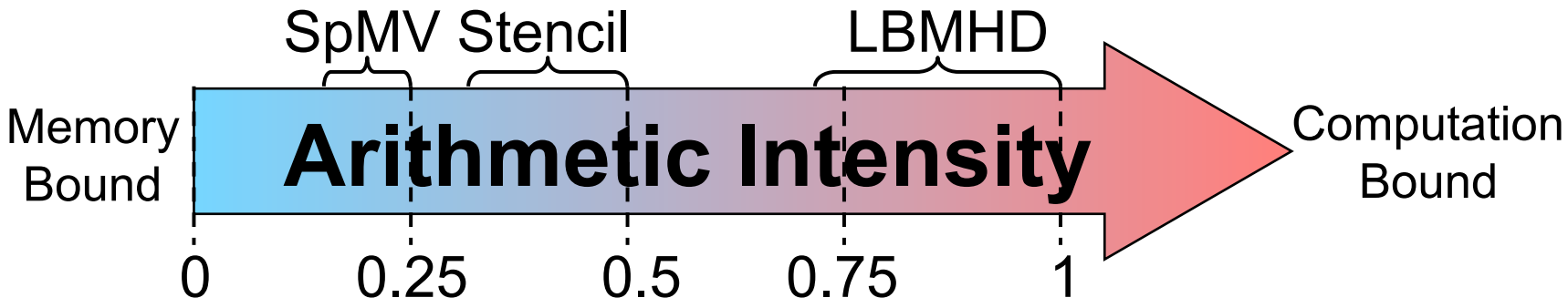
```
struct{
  // macroscopic quantities
  double * Density;
  double * Momentum[3];
  double * Magnetic[3];
  // distributions
  double * MomentumDist[27];
  double * MagneticDist[3][27];
}
```

(d) data structure

# Arithmetic Intensity
## (Ratio of flops to DRAM bytes)



- AI is rough indicator of whether kernel is memory or compute-bound
- Counting *only* compulsory misses:




- The range in AI values results from:
  - SpMV: the amount register blocking reduces redundant column indices
  - Stencil and LBMHD: whether the architecture is write-allocate
- Actual AI values are typically lower (due to other types of cache misses)

# Autotuning Strategy



- Autotuning provides a **portable** and effective method for tuning
- All three kernels used Perl scripts to generate code variants
- Implemented by Kaushik Datta and Sam Williams
- SpMV: Heuristic search
  - Chose best parameter values via heuristics
  - Example: Selected best matrix compression parameters by finding minimum matrix size
- LBMHD: Full exhaustive search
  - Relatively small search space allowed full exhaustive search using power-of-two values
- Stencil: “Greedy” exhaustive search
  - Large search space, so applied each optimization individually
  - Performed exhaustive search using power-of-two values within each optimization’s parameter space
  - Chose the best value before proceeding

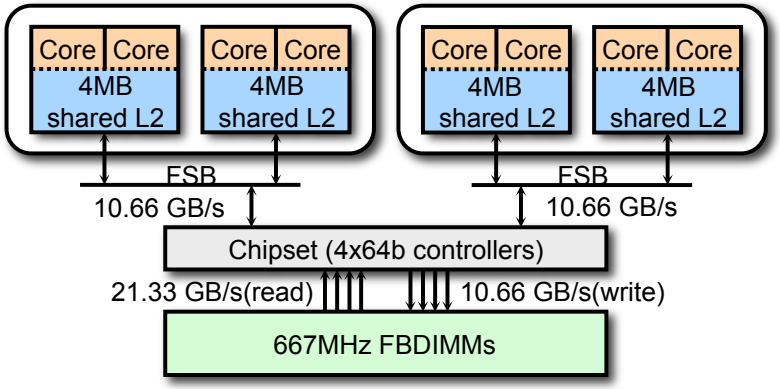
# Summary of Optimizations



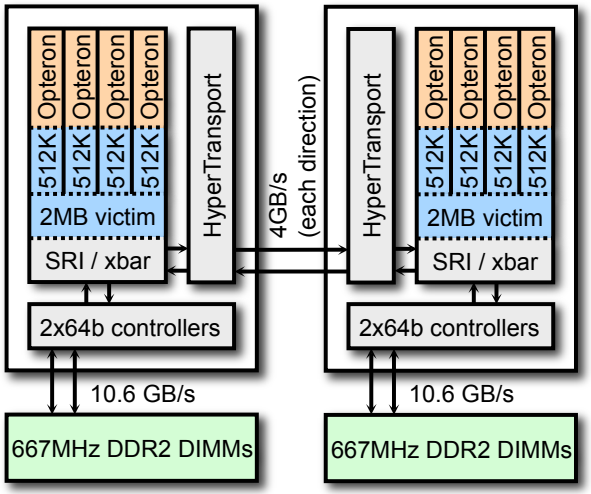
| No. | Optimization | OSKI 1.0.1h | Williams *etal.* |
|---|---|---|---|
| 1. | Register Blocking | ✓ | ✓ |
| 2. | Cache Blocking | ✓ | ✓ |
| 3. | Software Prefetching | | ✓ |
| 4. | Matrix Compression | | ✓ |
| 5. | Serial Benchmarking | ✓ | |
| 6. | Data Decomposition within Shared Memory | | ✓ |
| 7. | Parallel Benchmarking | | |
| 8. | Data Decomposition across Distributed Memory | | |
| 9. | SIMDization | | ✓ |
| 10. | Software Pipelining | | ✓ |
| 11. | TLB Blocking | | ✓ |

# Architectures

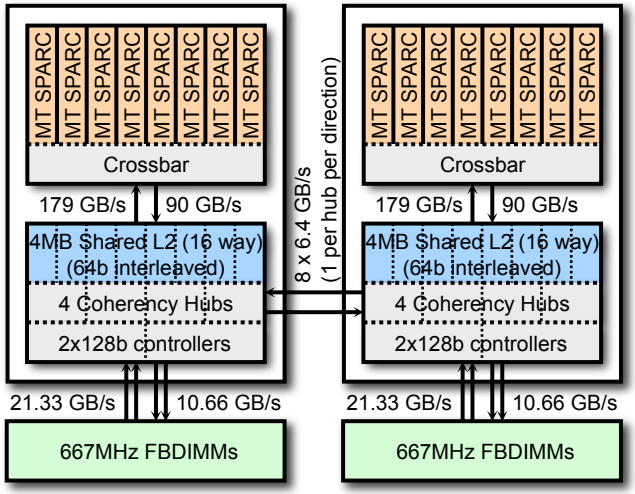




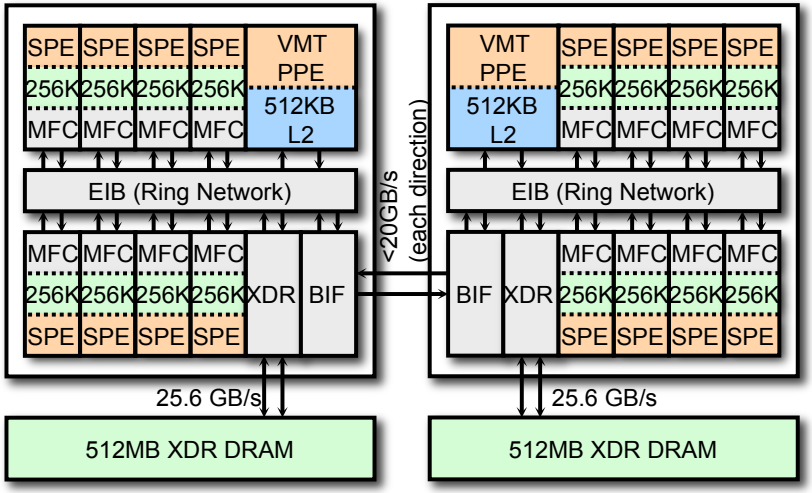

Intel Clovertown




AMD Barcelona




Sun Niagara2 (Victoria Falls)

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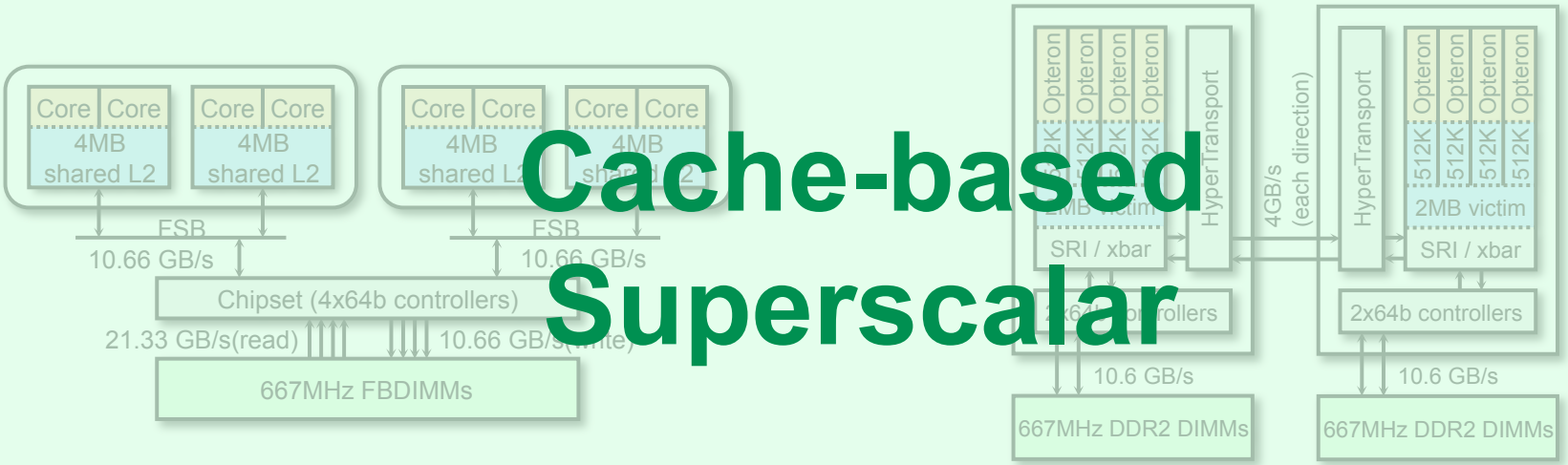
# Architectures
## (Architectural Features)






Cache-based Superscalar

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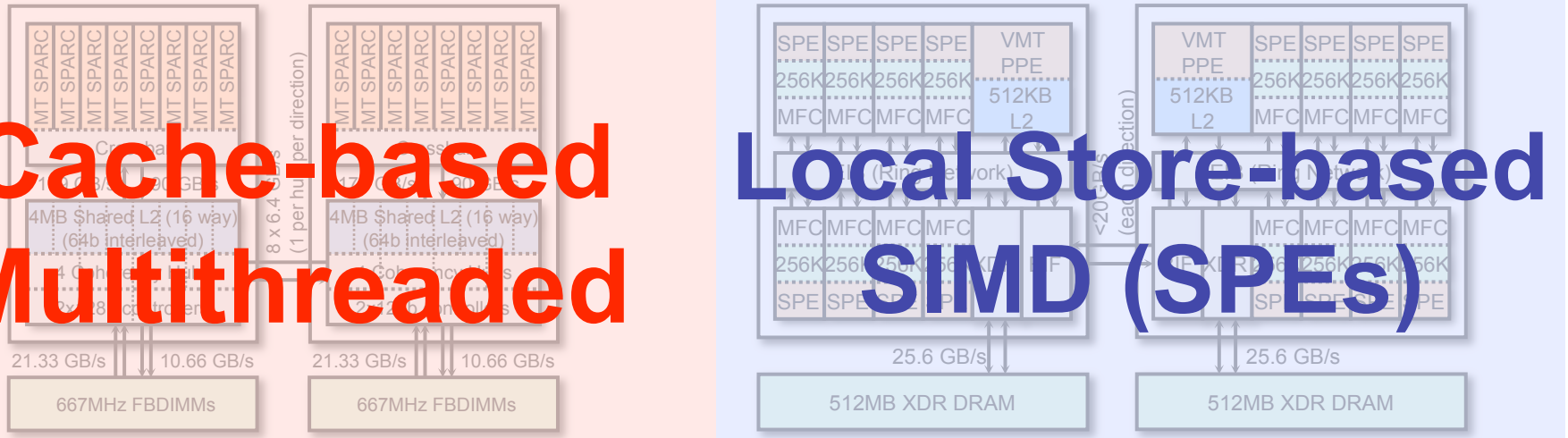


Cache-based Multithreaded

Local Store-based SIMD (SPEs)

Sun Niagara2 (Victoria Falls)

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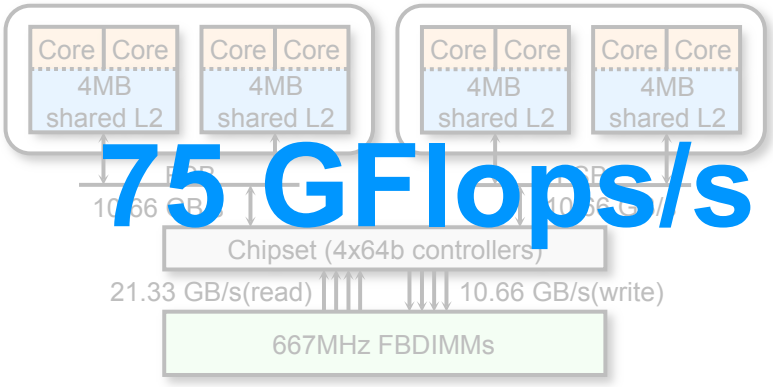
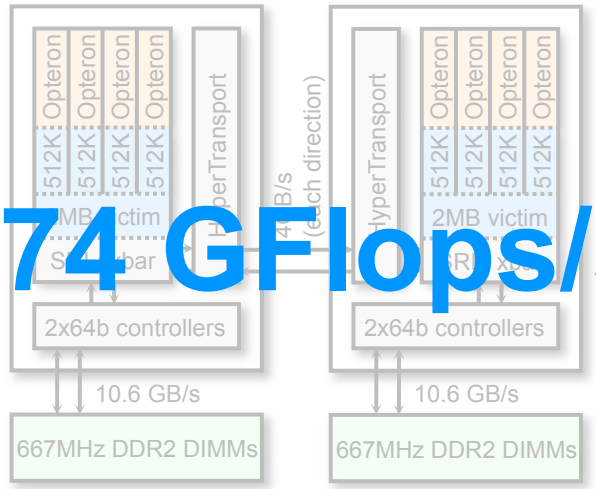
# Architectures
## (Double Precision Peak Flops)





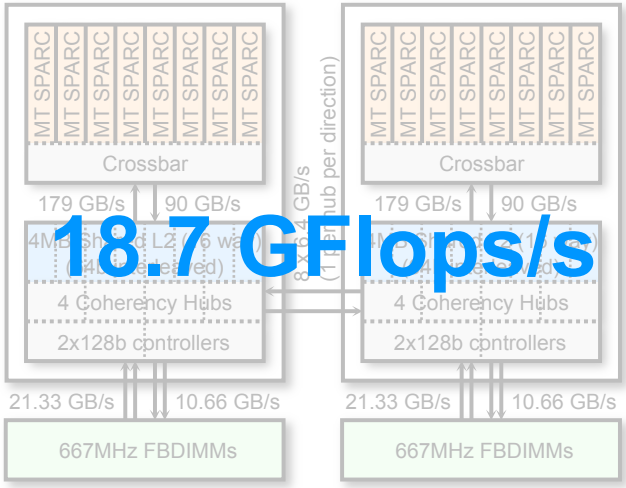

75 GFlops/s

Intel Clovertown



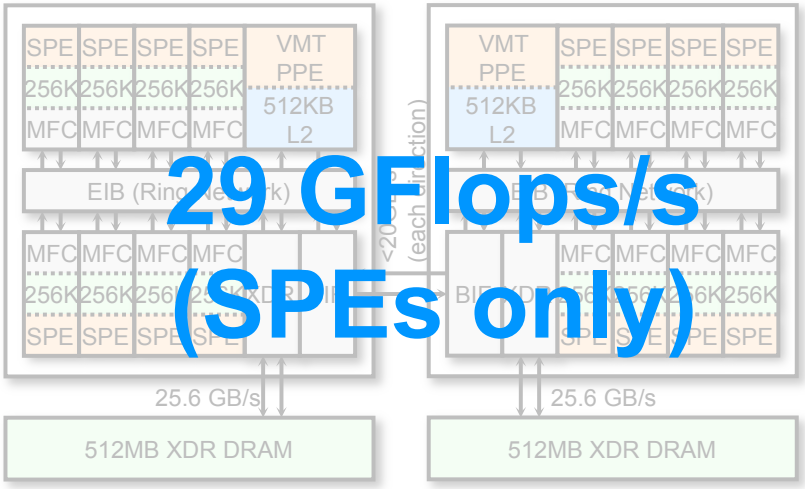

74 GFlops/s

AMD Barcelona




18.7 GFlops/s

Sun Niagara2 (Victoria Falls)




29 GFlops/s
(SPEs only)

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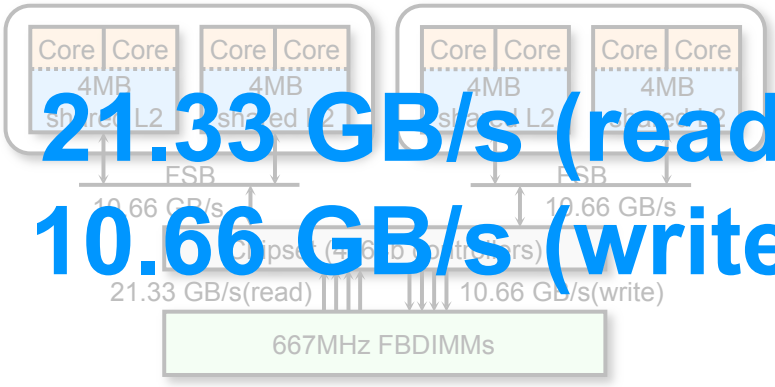
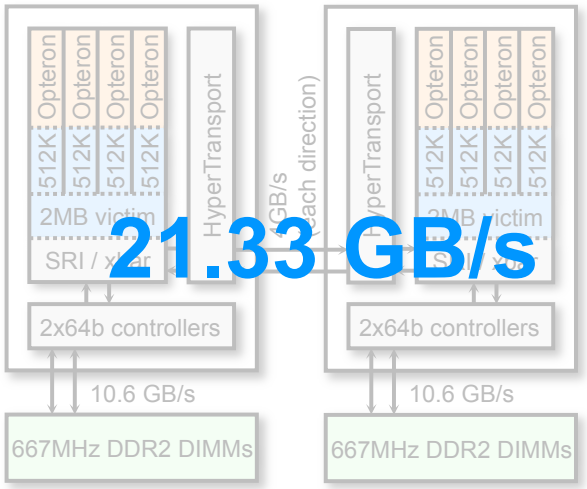
# Architectures
## (Raw DRAM Bandwidth)





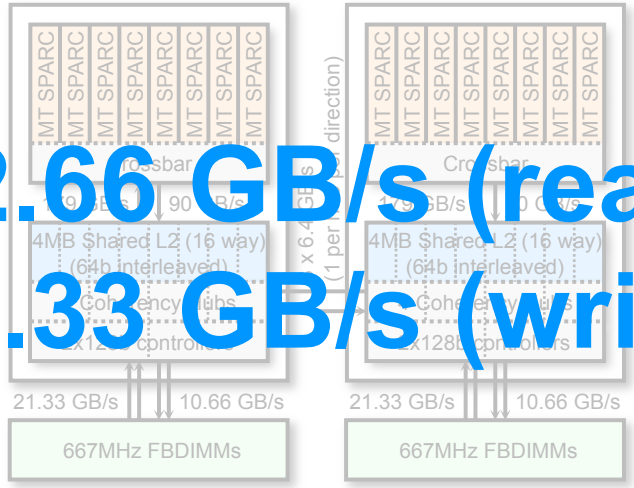

21.33 GB/s (read)
10.66 GB/s (write)

Intel Clovertown



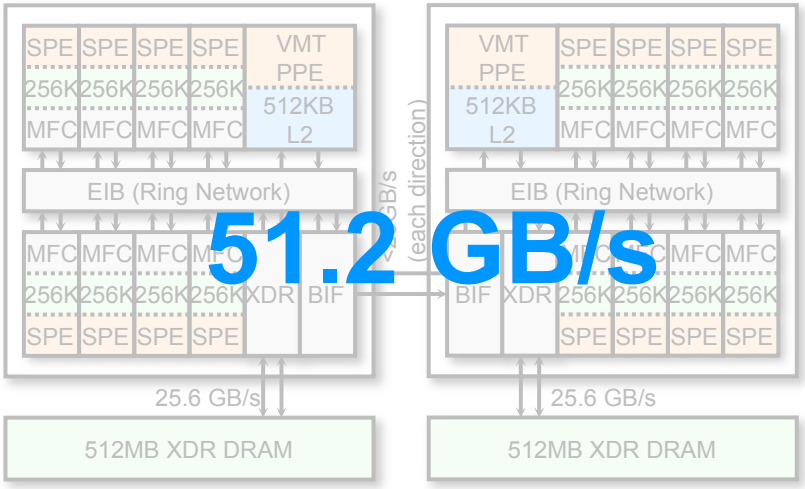

21.33 GB/s

AMD Barcelona




42.66 GB/s (read)
21.33 GB/s (write)

Sun Niagara2 (Victoria Falls)




51.2 GB/s

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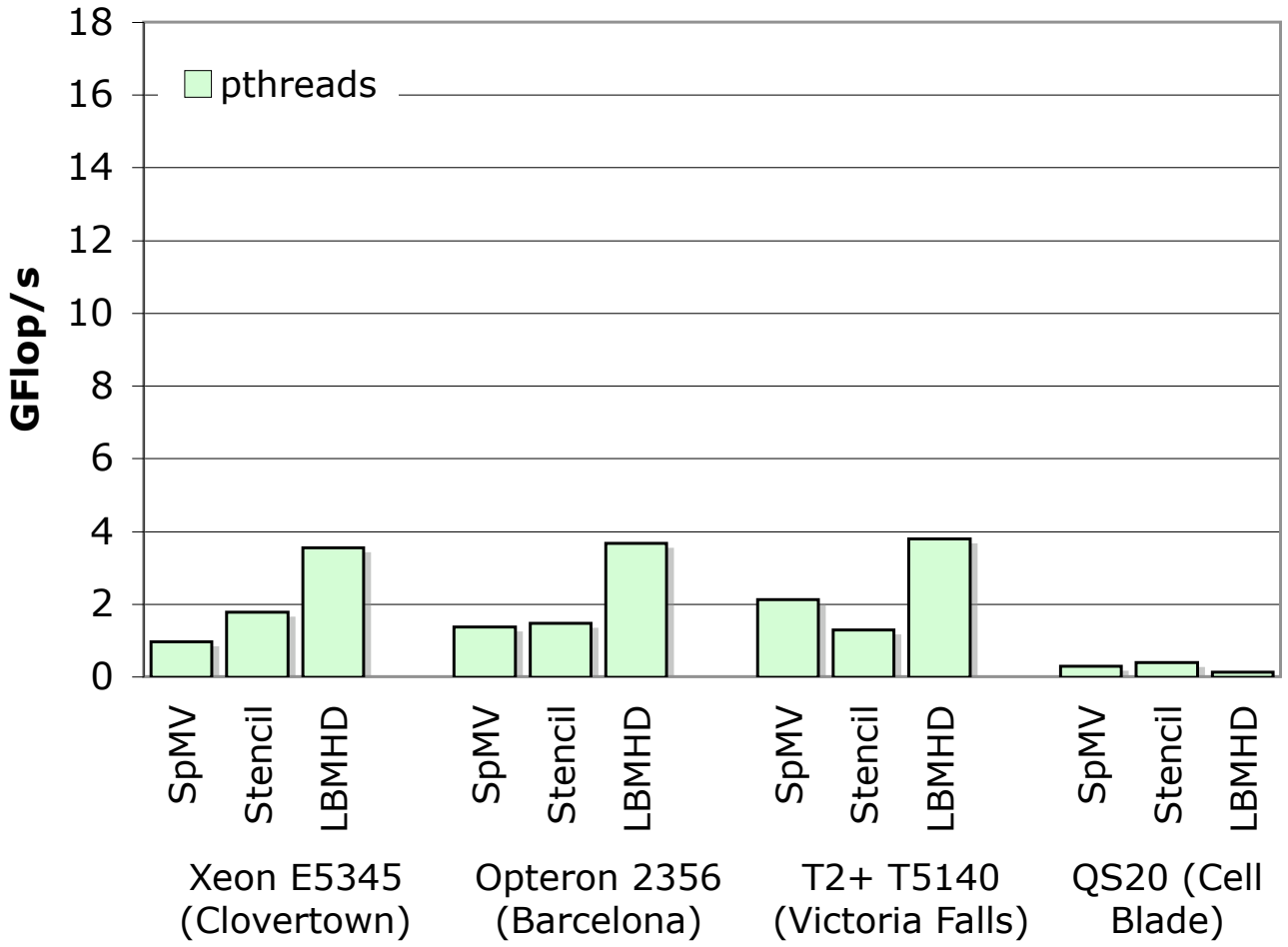
# Kernel Performance



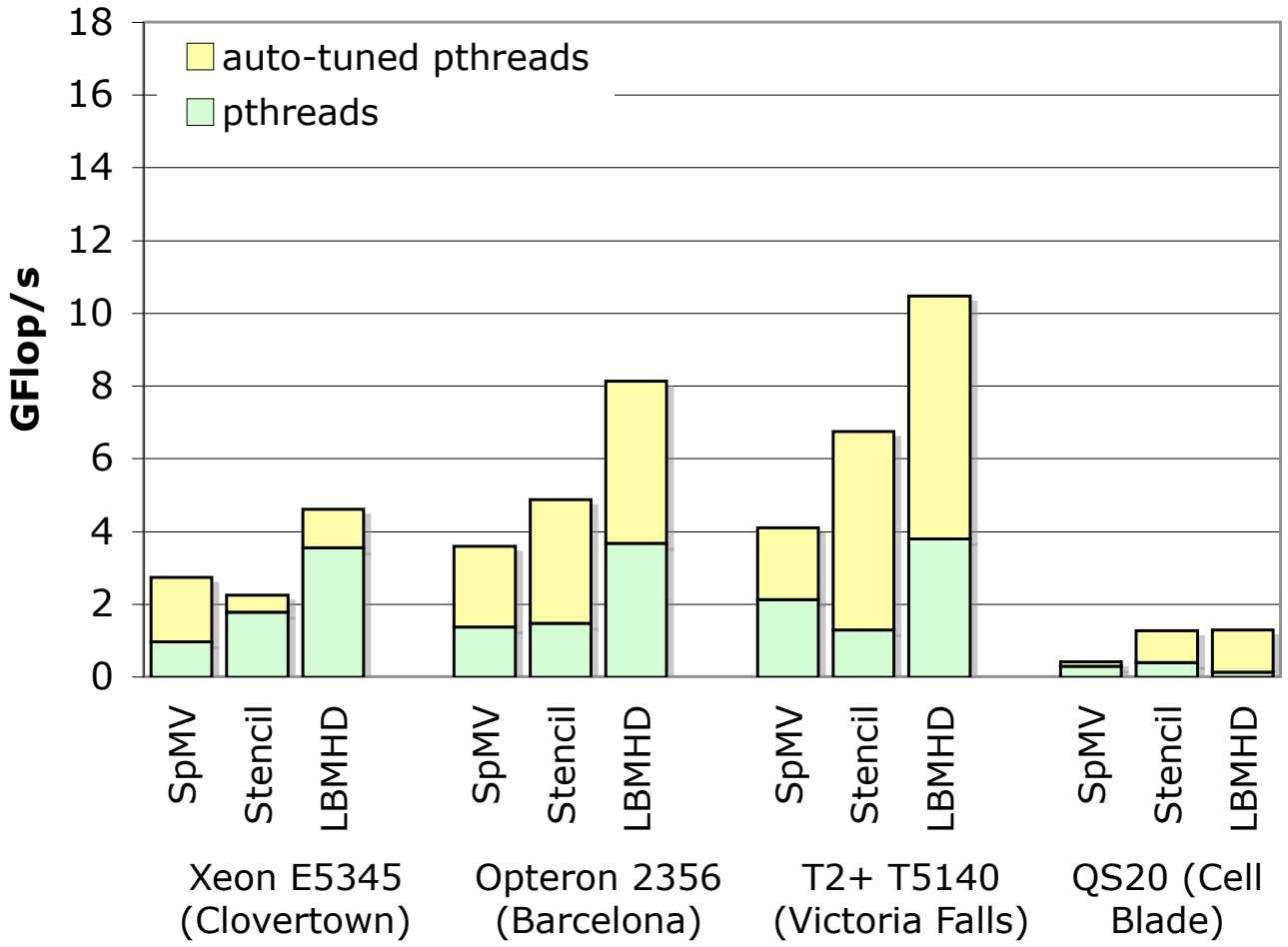



SpMV number is average over suite of matrices

- Naïve portable C code
- Little programmer effort
- Performance quality still unknown

# Kernel Performance

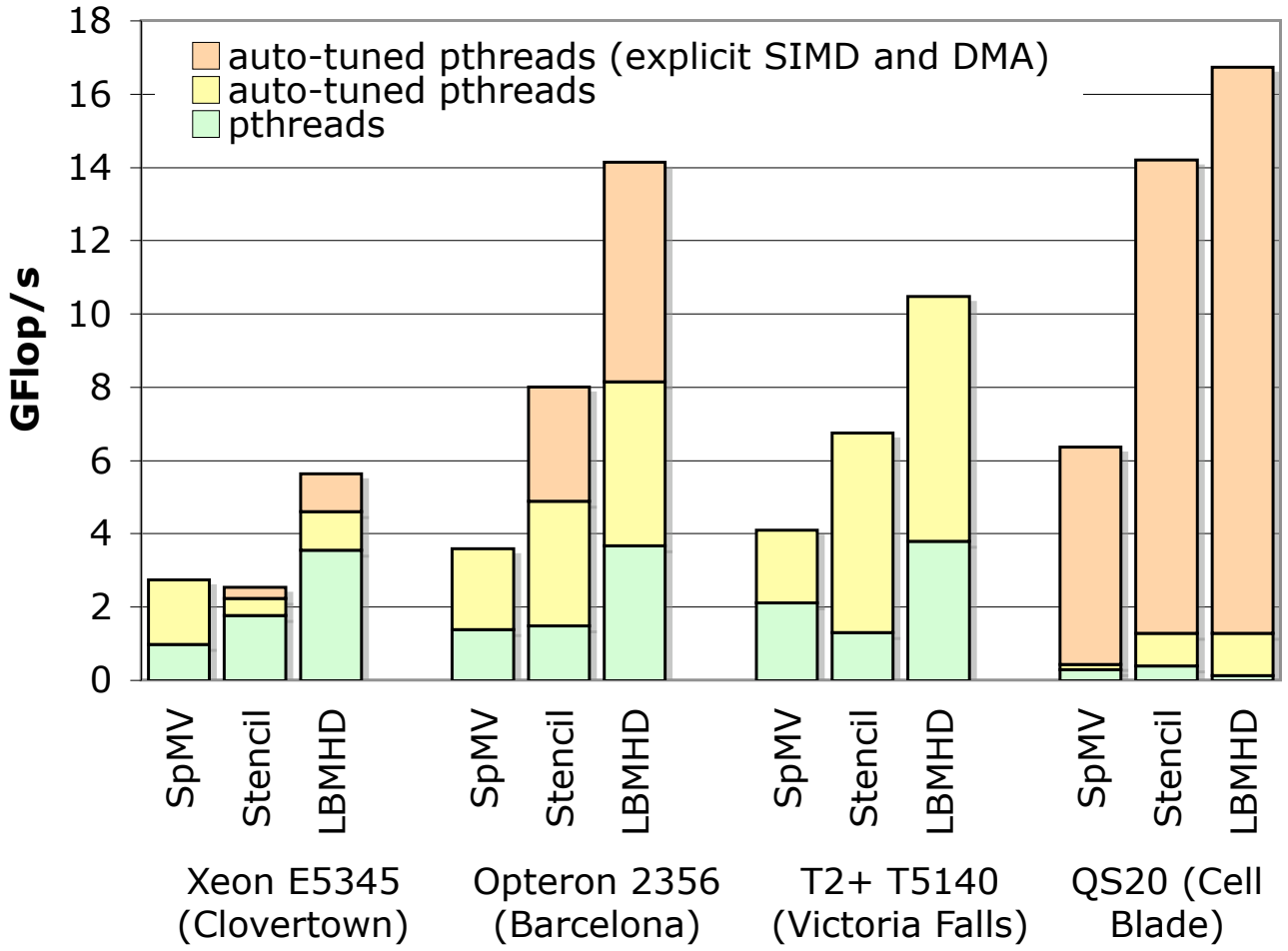





- Autotuned portable C code
- Significant programmer effort, but applicable across architectures
- Performance noticably improved on all machines

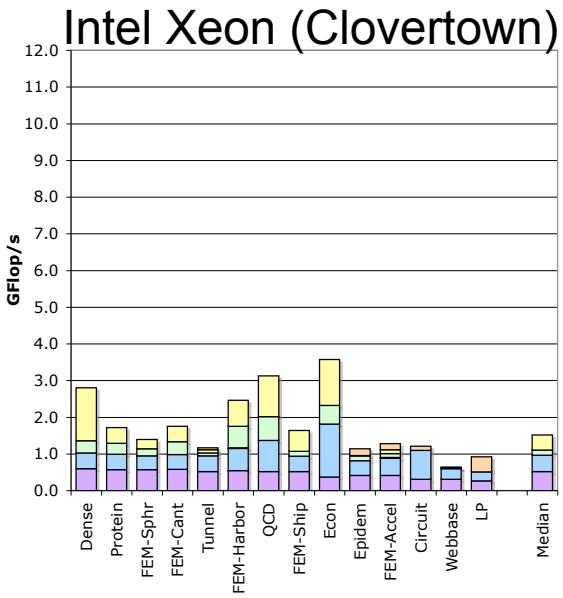
# Kernel Performance

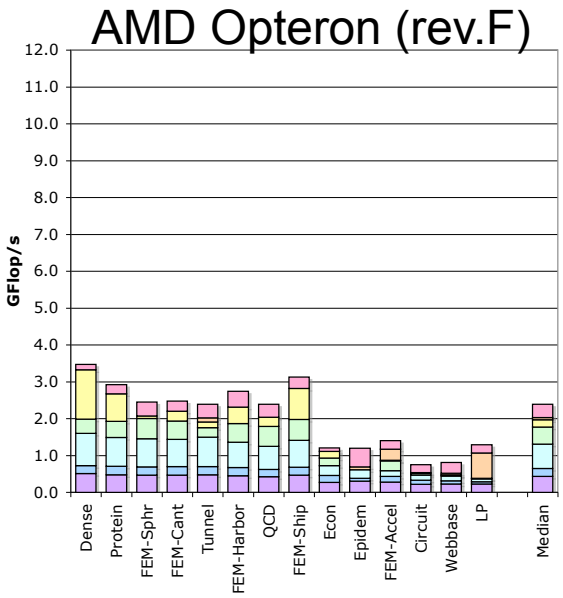


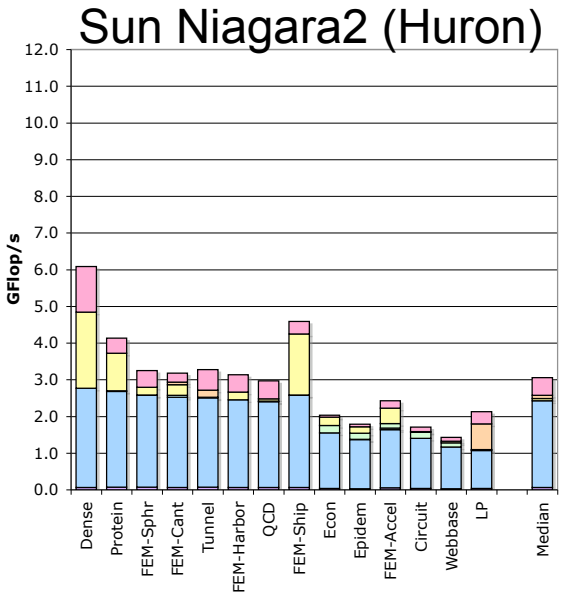


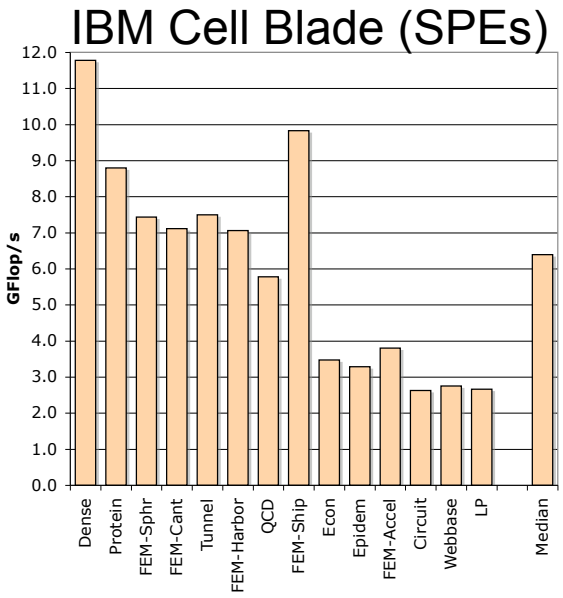

- Autotuned platform-specific C code
- Significant programmer effort for *each* architecture
- Performance dramatically improved on Cell (now using SPEs)

# SPMV Autotuned Performance

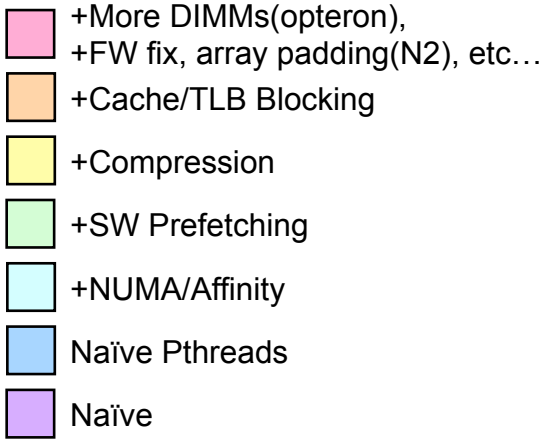



Note that different optimizations have different impacts per arch!



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  - Lattice Boltzmann MHD
  - Stencils (Heat Equation)
- Integrating SpMV Advances into OSKI
- Towards a framework for building autotuners
  - What is the role of the compiler?
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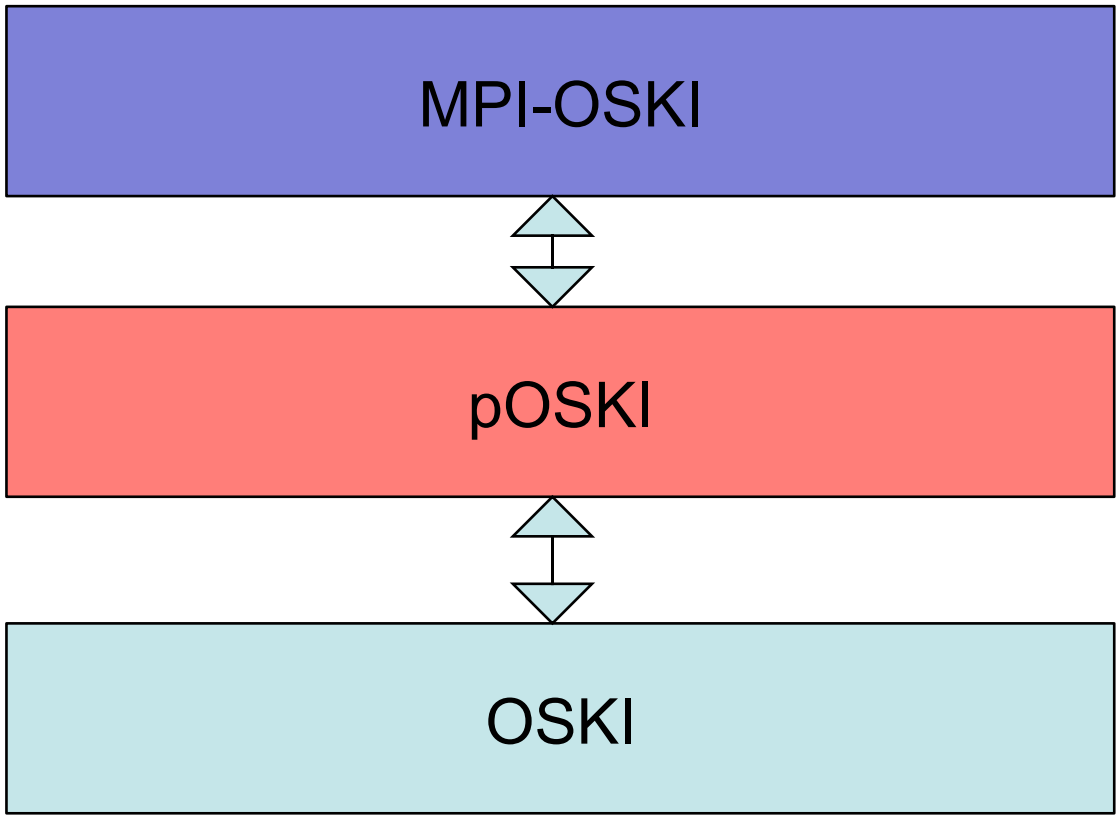
# OSKI Overview



- Optimized Sparse Kernel Interface (OSKI) by Rich Vuduc et al
  - autotuned library for sparse linear algebra (SpMV, TrSV, etc)
  - incorporated into PETSc
- Collection of low-level primitives that provides automatically tuned computational kernels on sparse matrices, for use by solver libraries and applications.
- Current implementation targets cache-based superscalar uniprocessor machines.
- Non-trivial run-time tuning cost for SpMV: up to ~40 mat-vecs
  - Dominated by conversion time
- Design point: user calls “tune” routine explicitly
  - Exposes cost
  - Tuning time limited using estimated workload
    - Provided by user or inferred by library
- The work presented here only optimizes SpMV execution.

# OSKI + pOSKI + MPI-OSKI






Goal: A system that works on single core, multicore, multisocket, CluMPs.

# Optimizations Added to OSKI



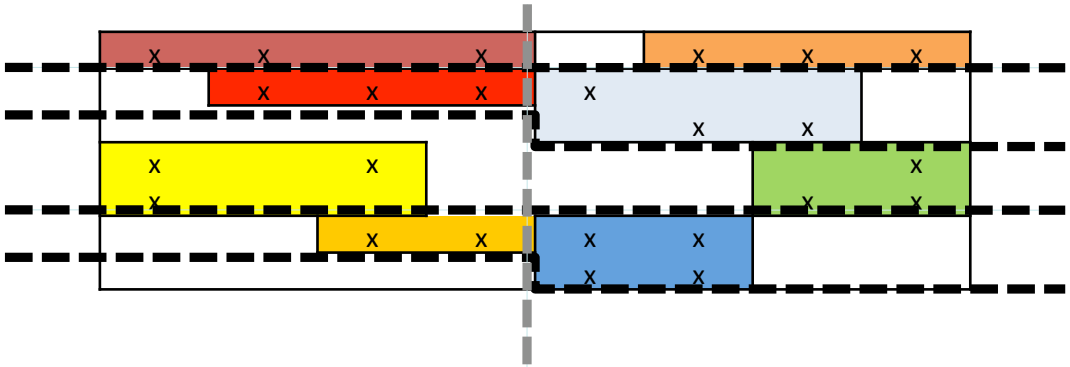
- Matrix Specific Allocation
  - Each matrix can have an associated allocator/deallocator and any auxiliary information
  - A parallel layer on top can provide NUMA-Aware allocator/deallocator and store thread information in the ‘info’ field
  - Important to preserve locality

- Prefetching
  - Prefetch Column Index and Values Array into cache
  - Prefetch distance currently fixed at 256 bytes ahead for Values Array and 128 bytes ahead for Column Index Array
  - Future version will tune over prefetch distance

# pOSKI



- Pthread Parallelization of OSKI by Ankit Jain
- Goal: Provide the optimizations presented in Williams, *et al.* in a distributable library for others to use.
- Data Decomposition
  - Exhaustive search over all combinations of data decompositions with available software threads (Limited to 32 for this study)
  - Threads load balanced by number of nonzeros
  - E.g: 4x2 Decomposition of a Matrix



- pBench
  - Run multiple instances of SpMV for a dense matrix stored in sparse format for all block sizes in parallel
  - Benchmarked for all powers of 2 threads up to 64

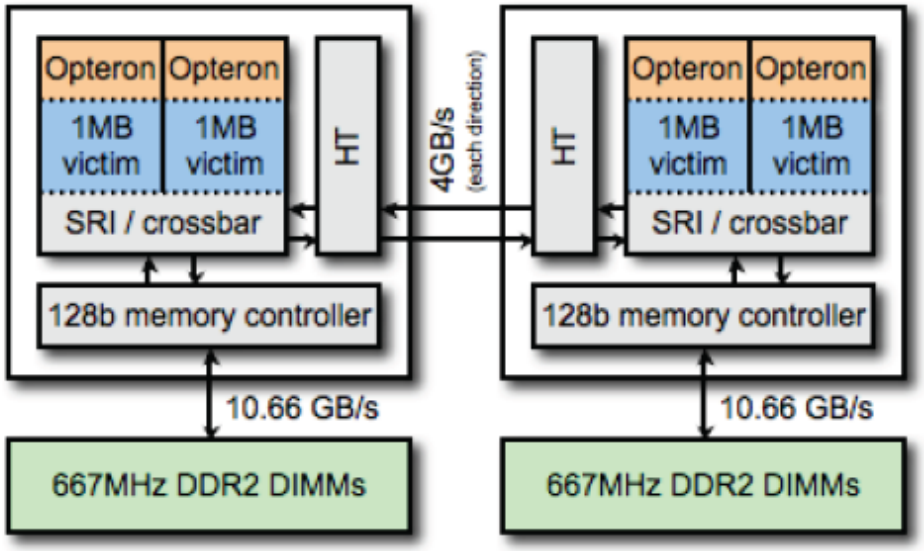
# Summary of Optimizations



| No. | Optimization | OSKI 1.0.1h | OSKI 1.1 | pOSKI | Williams *et al.* |
|---|---|---|---|---|---|
| 1. | Register Blocking | ✓ | ✓ | | ✓ |
| 2. | Cache Blocking | ✓ | ✓ | | ✓ |
| 3. | Software Prefetching | | ✓ | | ✓ |
| 4. | Matrix Compression | | (✓) | | ✓ |
| 5. | Serial Benchmarking | ✓ | ✓ | | |
| 6. | Data Decomposition within Shared Memory | | | ✓ | ✓ |
| 7. | Parallel Benchmarking | | | ✓ | |
| 8. | Data Decomposition across Distributed Memory | | | | |
| 9. | SIMDization | | | | ✓ |
| 10. | Software Pipelining | | | | ✓ |
| 11. | TLB Blocking | | | | ✓ |

# Architecture Studied

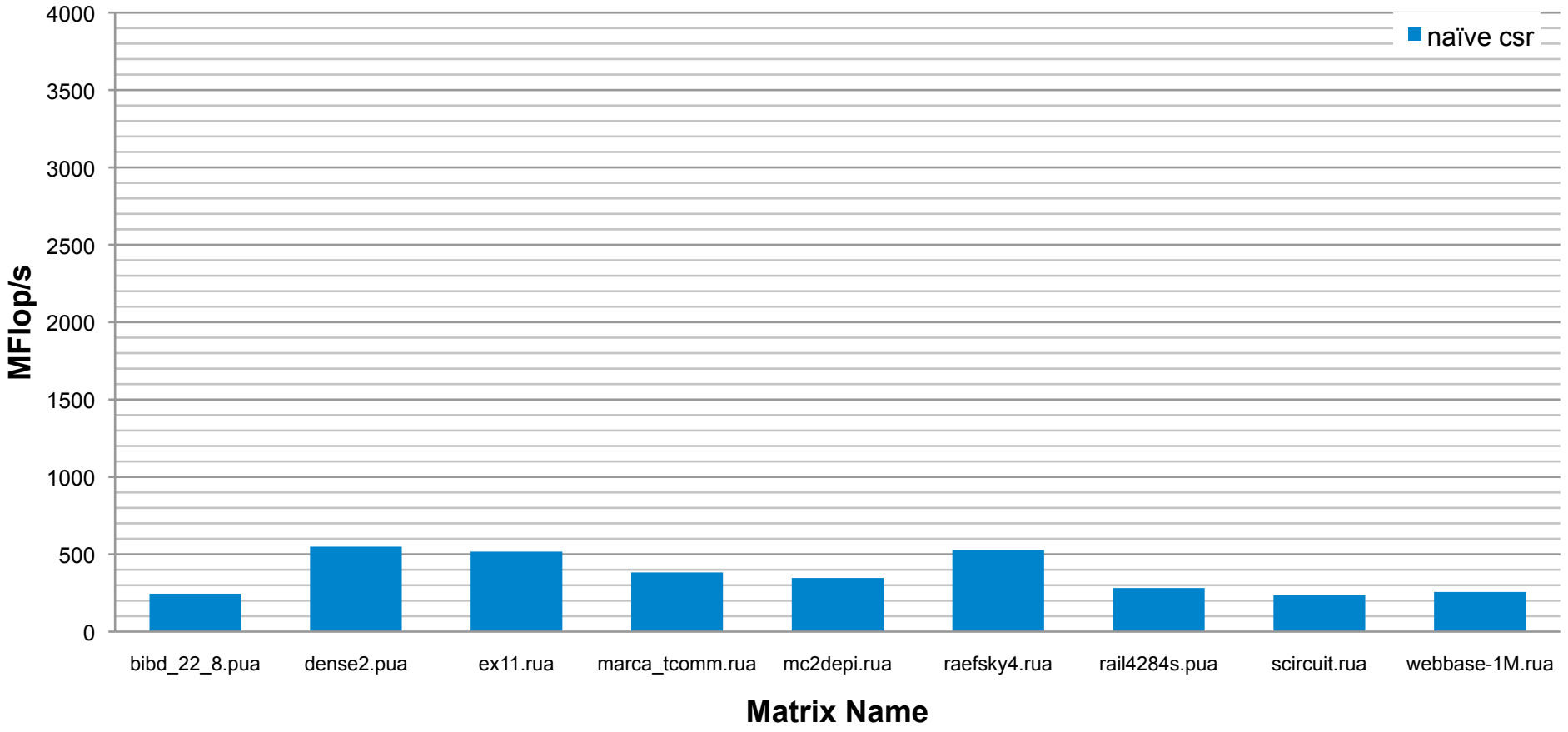





AMD Opteron X2

# Preliminary Results





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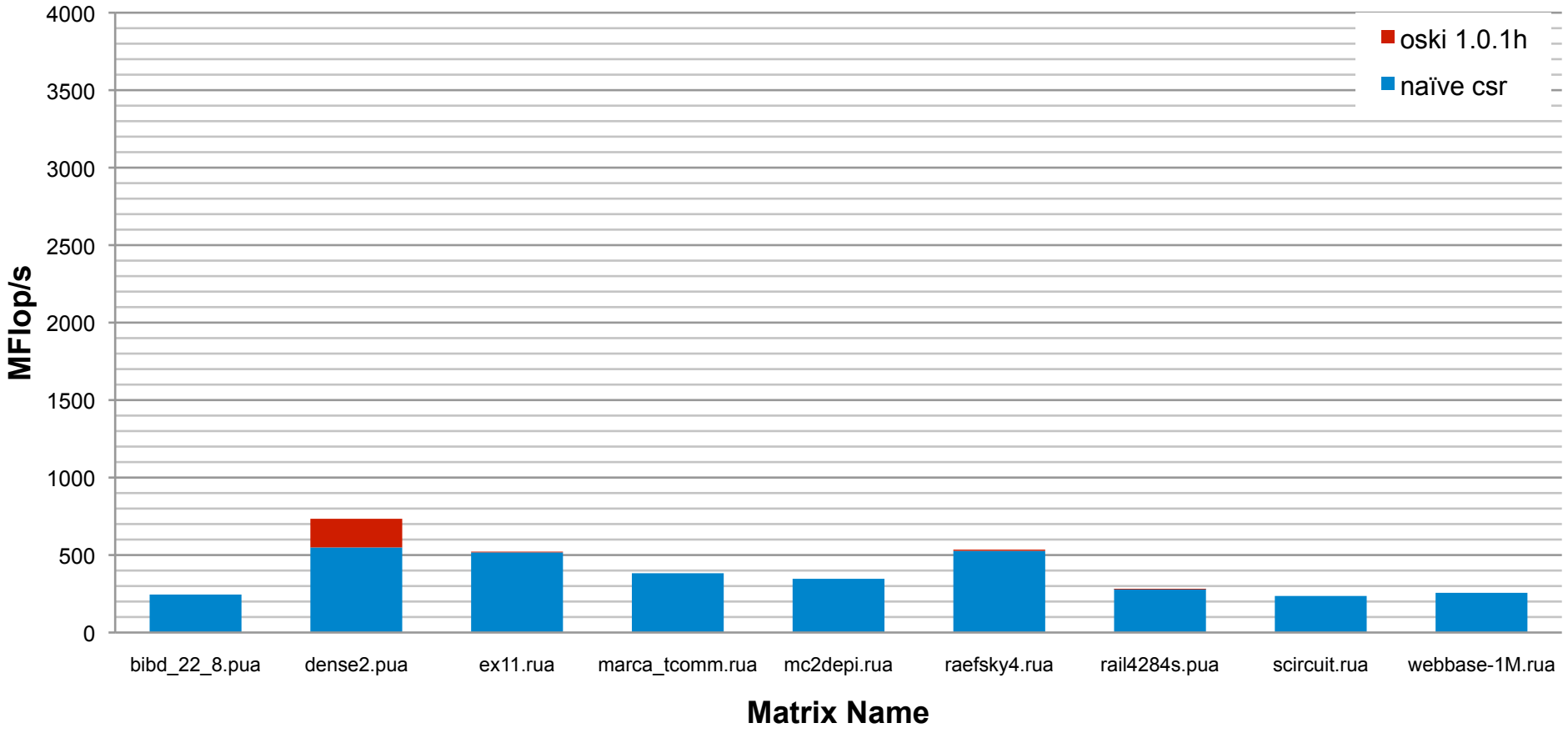

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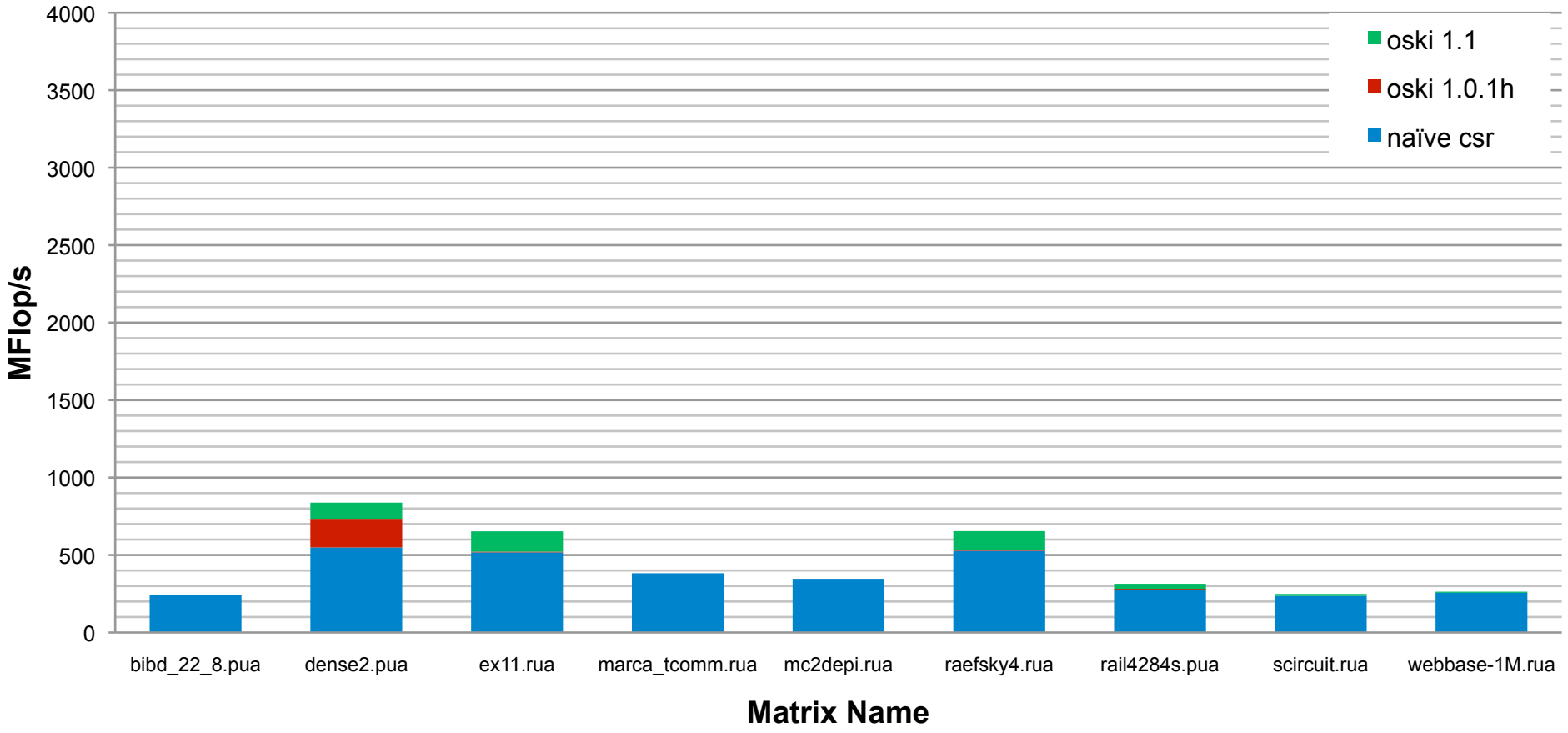

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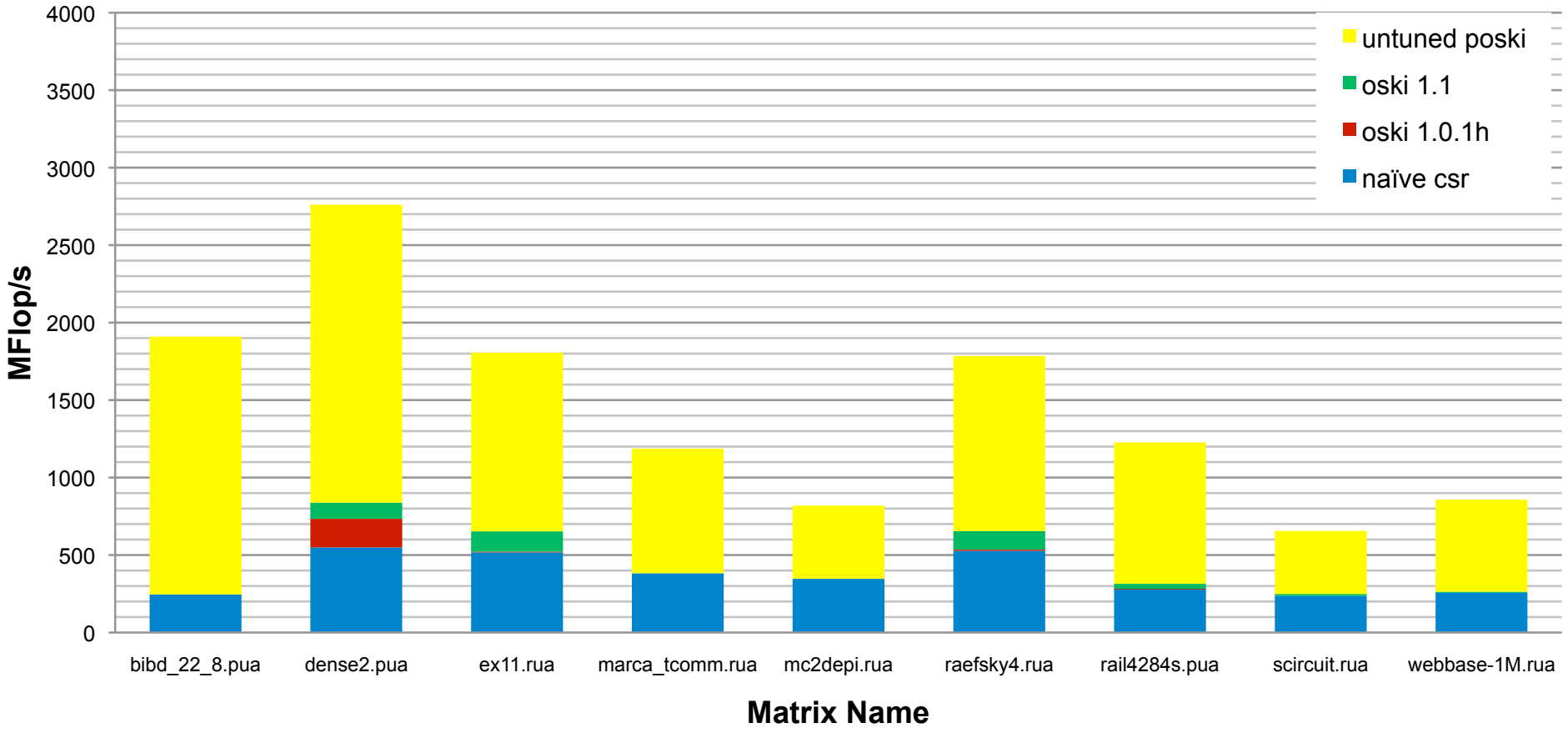
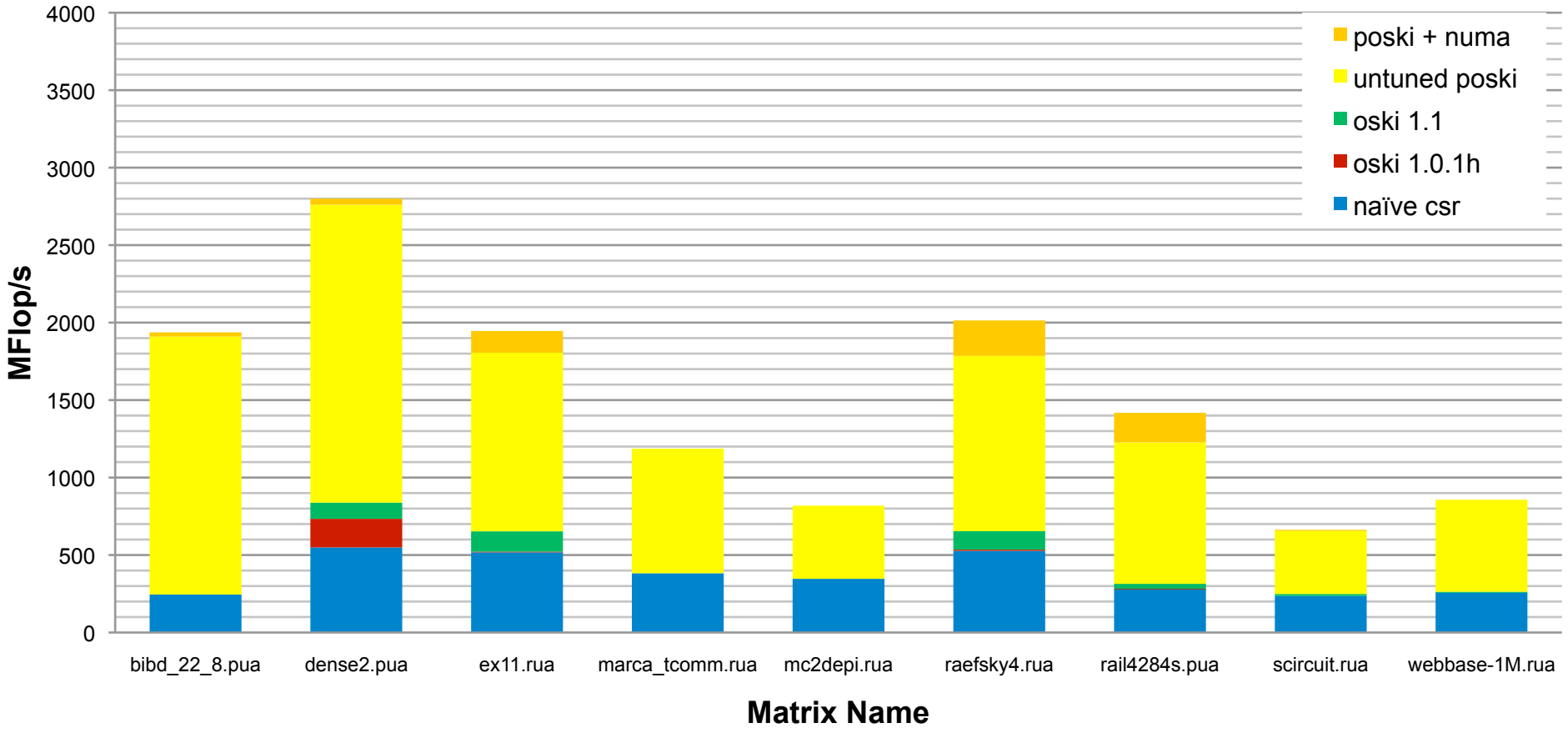



"Untuned pOSKI" uses tuned OSKI, but no tuning at the pOSKI layer

# Preliminary Results

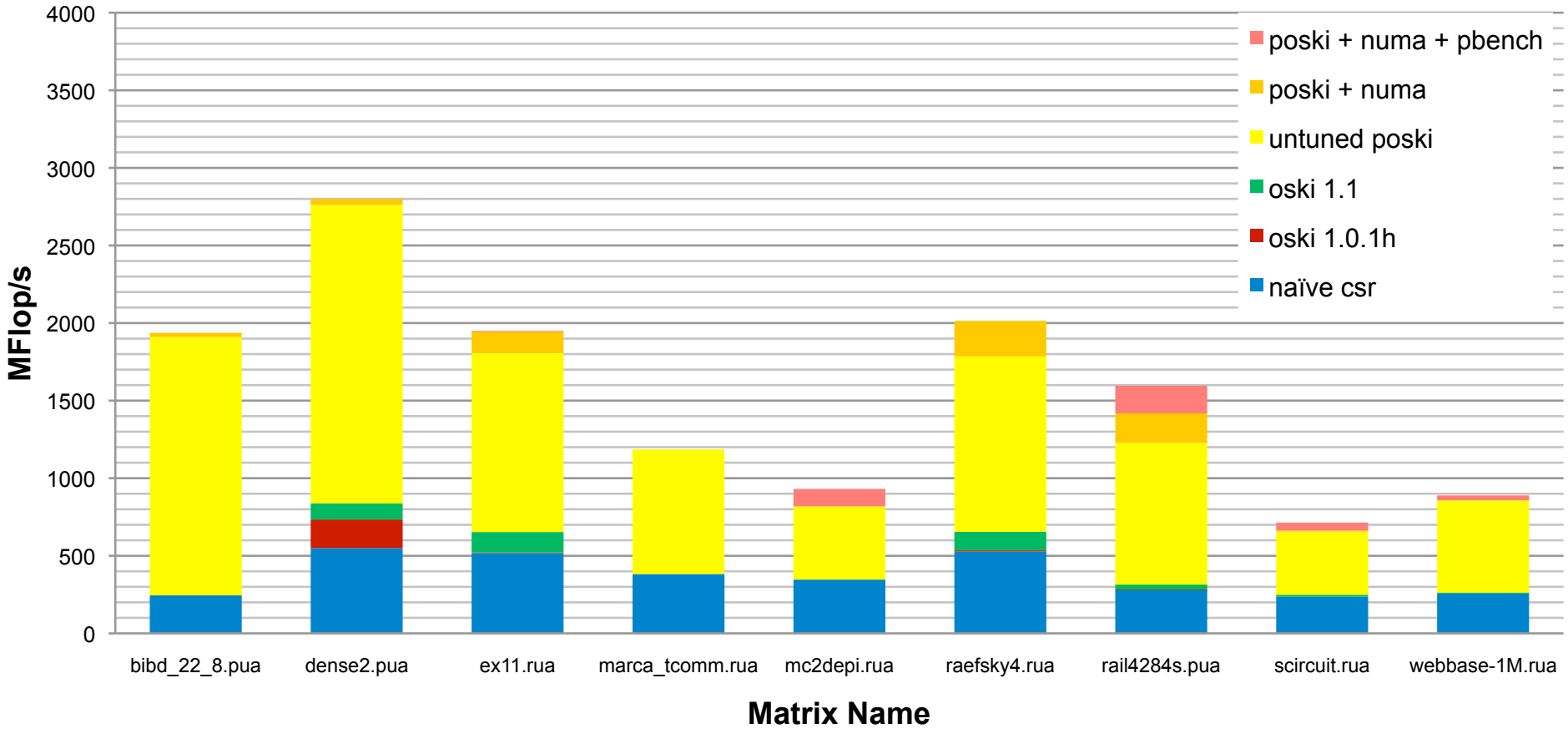




EECS
Electrical Engineering and Computer Sciences

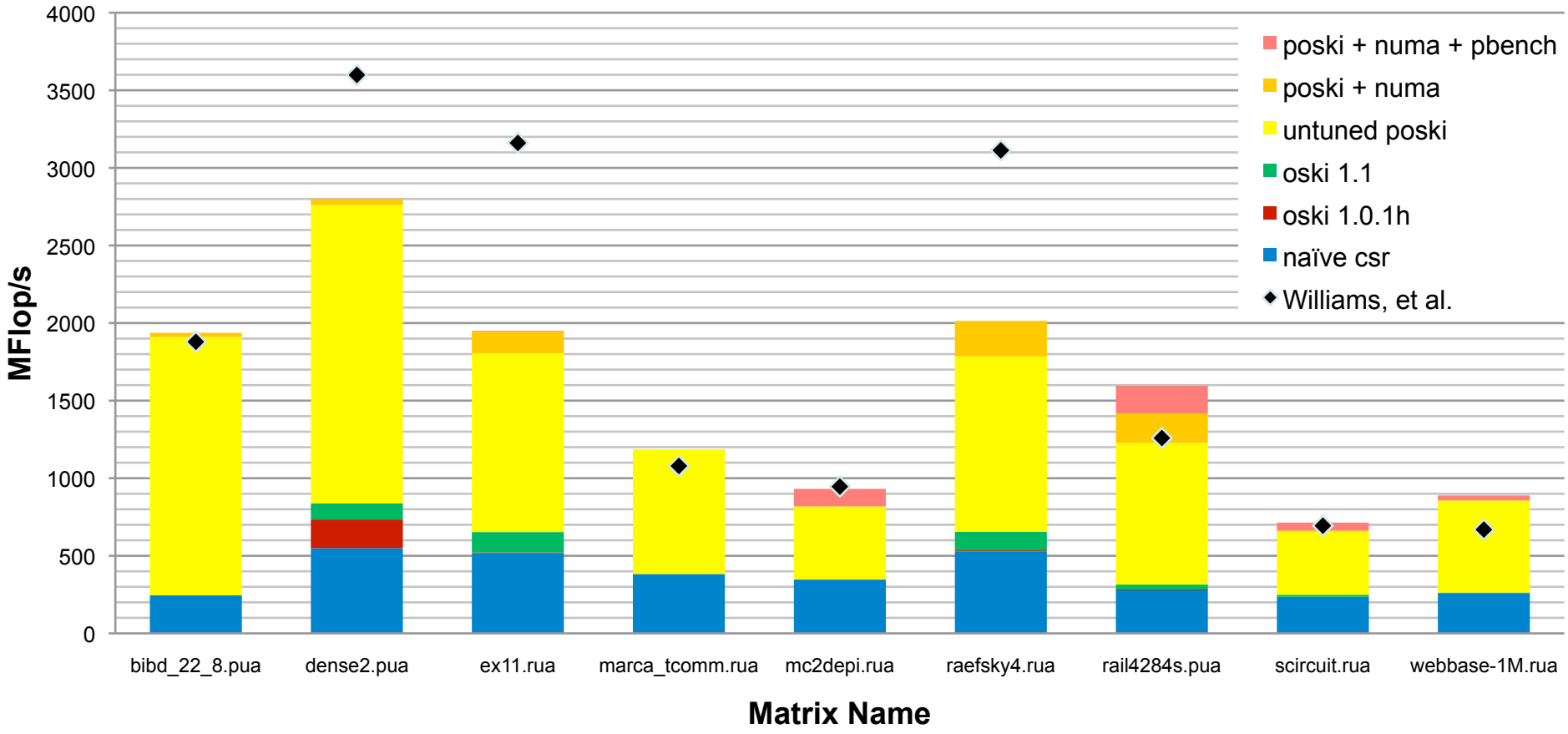
# Preliminary Results

BERKELEY PAR LAB



# Preliminary Results





# Coming Soon…



- Search over Prefetch Distances
  - During serial tuning step
  - Optimal distance has been found to be matrix specific
- Add Matrix Compression to OSKI since it is the next most effective optimization
- Collect Data on other systems
  - Currently building pOSKI on Intel Xeon(Clovertown) and Sun Victoria Falls(Maramba)
- A release of pOSKI

# Overview



- Other autotuning at Berkeley
- Recent work autotuning three parallel kernels
  - Sparse Matrix Vector Multiply (SpMV)
  - Lattice Boltzmann MHD
  - Stencils (Heat Equation)
- Integrating SpMV Advances into OSKI
- Towards a framework for building autotuners
  - What is the role of the compiler?
- Open questions

# Common Optimizations



- Threading and Parallelization
  - Thread blocking
- Maximizing in-core performance
  - Loop unrolling/reordering
  - SIMDization
- Maximizing memory bandwidth
  - Limiting number of memory streams
  - NUMA-Aware (collocating data with processing threads)
  - Software prefetching
- Minimizing memory traffic (Addressing 3 C's model)
  - Padding (Conflict misses)
  - Cache blocking (Capacity misses)
  - Cache bypass (via intrinsic for x86) (Compulsory misses)

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# Why Are We Autotuning Then?



- Domain-specific knowledge gives more information than is available from just the source code
  - e.g. guaranteed no aliasing, ATLAS anecdotes, SpMV unique indirection
- "The focus on specialized tuning systems is too narrow, and so only compilers, which apply most broadly, are the most sensible investment."
  - Yes and No.
- "What can we do to build common tool bases for compiler-based autotuning and for construction of self-tuning or autotuning libraries?"
  - Leverage compiler infrastructure
  - Compiler & autotuning community must cooperate
- "Self-tuned libraries will always outperform compiler-generated code."
  - cooperatively-tuned libraries/code will perform better than "self-tuning" alone or "compiler-generated" alone

# What I Want



## An Expert Interface to the Compiler

- Use existing compiler infrastructure + domain knowledge
- Parsing, AST transformations, SIMDization, code generation
  - I don't want to replicate these
  - I want to add my own transformations or SIMDization logic
- Are pragmas enough?

- For my autotuning project, I need all of these capabilities!

# What issues are we as a community ignoring?



- Different metrics for success
  - Power.
- Composition/scheduling
  - how can all these autotuned libraries + autotuners + compilers work together if each piece of code is tuned independently?
- Usability!
  - Code availability & licensing, platform independence
  - Does it actually compile
  - Is the pain worth the performance improvement