Optimizations & Bounds for Sparse Symmetric Matrix-Vector Multiply

Berkeley Benchmarking and Optimization Group (BeBOP)

http://bebop.cs.berkeley.edu

Benjamin C. Lee, Richard W. Vuduc, James W. Demmel, Katherine A. Yelick University of California, Berkeley

27 February 2004

Outline

- Performance Tuning Challenges
- Performance Optimizations
 - Matrix Symmetry
 - Register Blocking
 - Multiple Vectors
- Performance Bounds Models
- Experimental Evaluation
 - 7.3x max speedup over reference (median: 4.2x)
- Conclusions

Introduction & Background

Computational Kernels

- Sparse Matrix-Vector Multiply (SpMV): $y \leftarrow y + A \cdot x$
 - A: Sparse matrix, symmetric (i.e. $A = A^T$)
 - x,y: Dense vectors
- Sparse Matrix-Multiple Vector Multiply (SpMM): $Y \leftarrow Y + A \cdot X$
 - X,Y: Dense matrices

Performance Tuning Challenges

- Sparse code characteristics
 - High bandwidth requirements (matrix storage overhead)
 - Poor locality (indirect, irregular memory access)
 - Poor instruction mix (low ratio of flops to memory operations)
- SpMV performance less than 10% of machine peak
- Performance depends on kernel, matrix and architecture

Optimizations: Matrix Symmetry

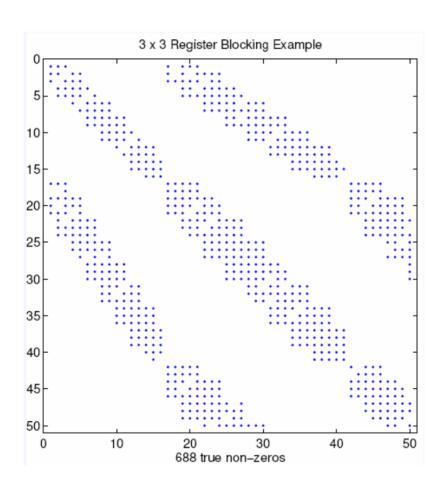
Symmetric Storage

- Assume compressed sparse row (CSR) storage
- Store half the matrix entries (e.g., upper triangle)

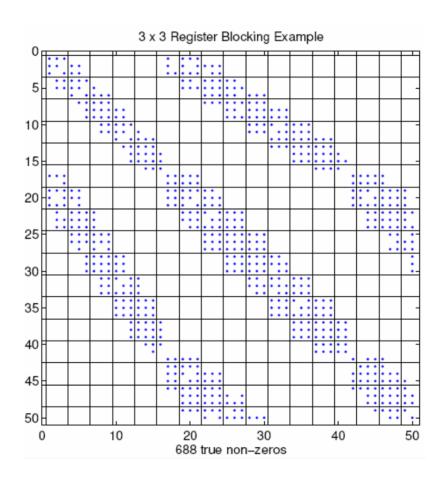
Performance Implications

- Same flops
- Halves memory accesses to the matrix
- Same irregular, indirect memory accesses
 - For each stored non-zero A(i, j)
 - y(i) += A(i,j) * x(j)
 - y(j) += A(i,j) * x(i)
- Special consideration of diagonal elements

Optimizations: Register Blocking (1/3)

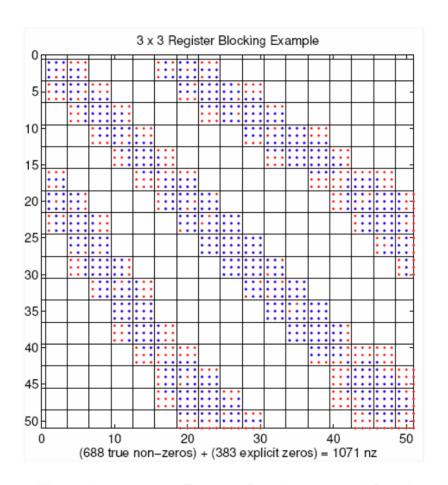


Optimizations: Register Blocking (2/3)



BCSR with uniform, aligned grid

Optimizations: Register Blocking (3/3)

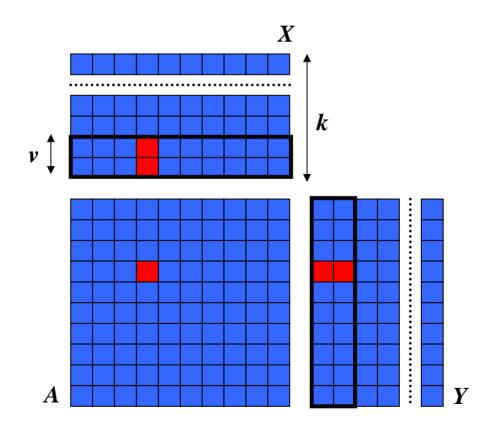


- Fill-in zeros: Trade extra flops for better blocked efficiency
 - In this example: 1.5x speedup with 50% fill on Pentium III

Optimizations: Multiple Vectors

Performance Implications

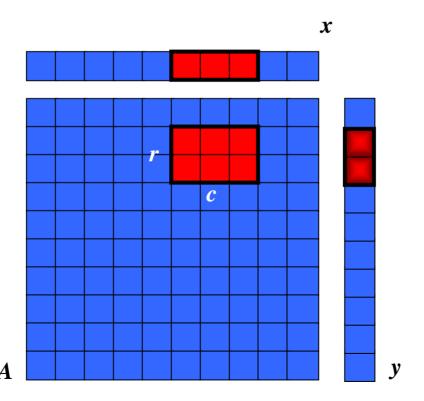
- Reduces loop overhead
- Amortizes the cost of reading A for v vectors



Optimizations: Register Usage (1/3)

Register Blocking

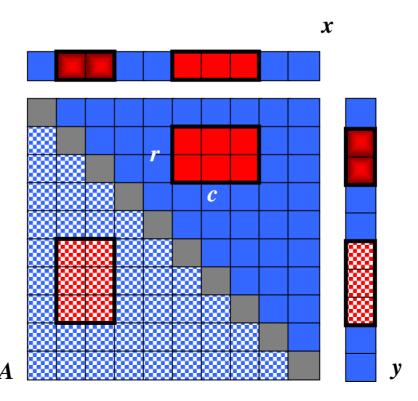
- Assume column-wise unrolled block multiply
- Destination vector elements in registers (r)



Optimizations: Register Usage (2/3)

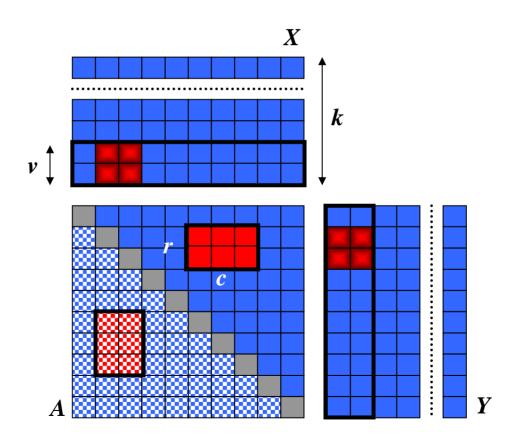
Symmetric Storage

- Doubles register usage (2r)
 - Destination vector elements for stored block
 - Source vector elements for transpose block



Optimizations: Register Usage (3/3)

- Vector Blocking
 - Scales register usage by vector width (2rv)



Performance Models

Upper Bound on Performance

Evaluate quality of optimized code against bound

Model Characteristics and Assumptions

- Consider only the cost of memory operations
- Accounts for minimum effective cache and memory latencies
- Consider only compulsory misses (i.e. ignore conflict misses)
- Ignores TLB misses

Execution Time Model

- Cache misses are modeled and verified with hardware counters
- Charge α_i for hits at each cache level
 - $T = (L1 \ hits) \ \alpha_1 + (L2 \ hits) \ \alpha_2 + (Mem \ hits) \ \alpha_{mem}$
 - $T = (Loads) \alpha_1 + (L1 \text{ misses})(\alpha_2 \alpha_1) + (L2 \text{ misses})(\alpha_{mem} \alpha_2)$

Evaluation: Methodology

Four Platforms

Sun Ultra 2i, Intel Itanium, Intel Itanium 2, IBM Power 4

Matrix Test Suite

- Twelve matrices
- Dense, Finite Element, Assorted, Linear Programming

Reference Implementation

- Non-symmetric storage
- No register blocking (CSR)
- Single vector multiplication

Evaluation: Observations

Performance

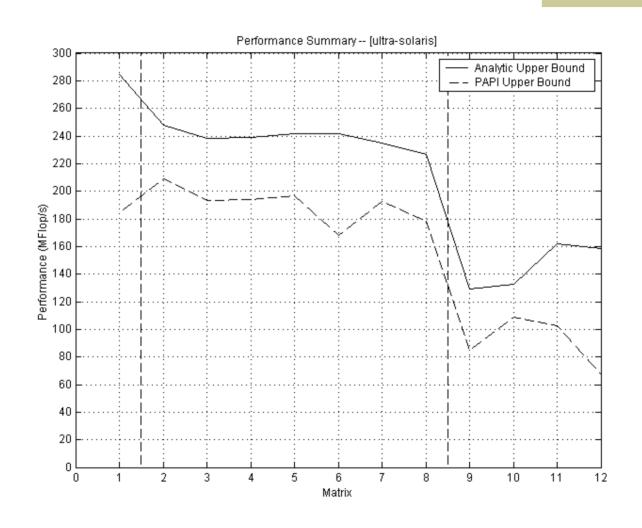
- 2.6x max speedup (median: 1.1x) from symmetry
 - {Symmetric BCSR Multiple Vector} vs. {Non-Symmetric BCSR Multiple Vector}
- 7.3x max speedup (median: 4.2x) from combined optimizations
 - {Symmetric BCSR Multiple Vector} vs. {Non-symmetric CSR Single Vector}

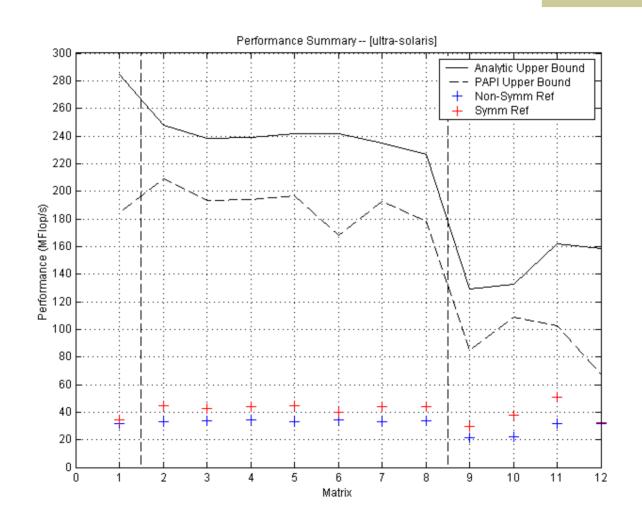
Storage

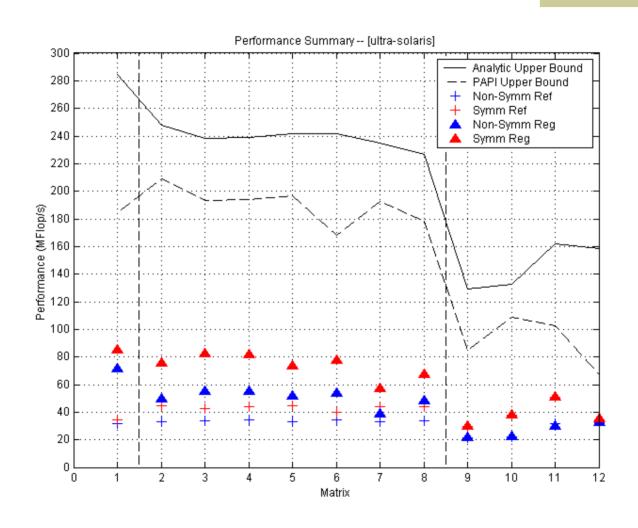
- 64.7% max savings (median: 56.5%) in storage
 - Savings > 50% possible when combined with register blocking
- 9.9% increase in storage for a few cases
 - Increases possible when register block size results in significant fill

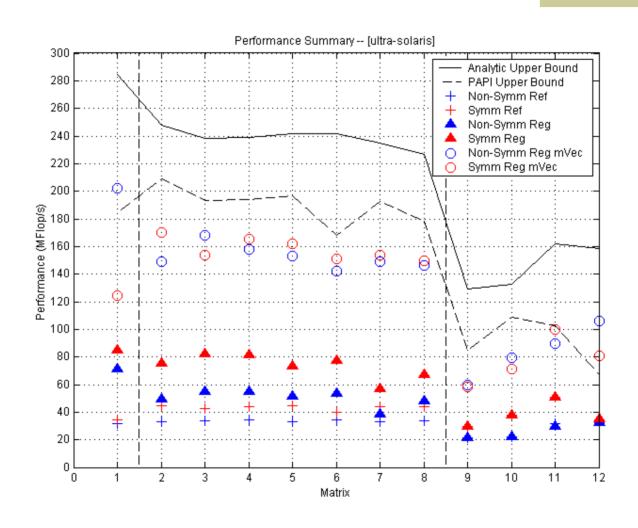
Performance Bounds

Measured performance achieves 68% of PAPI bound, on average

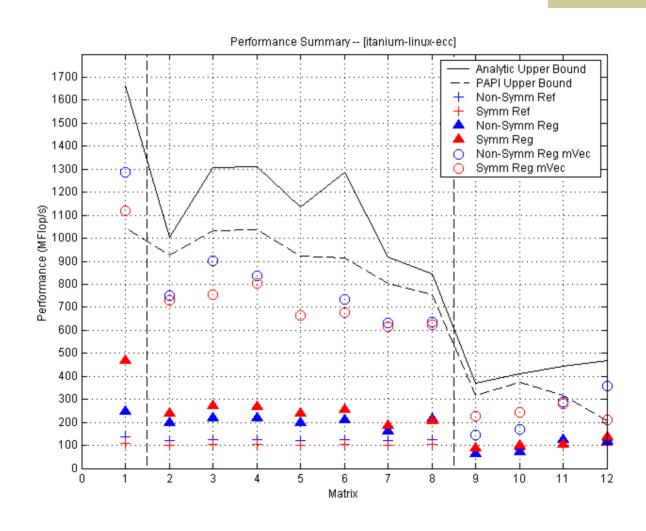




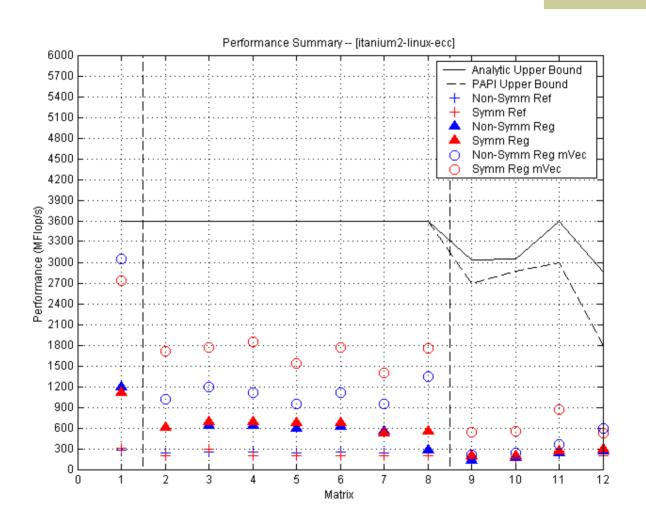




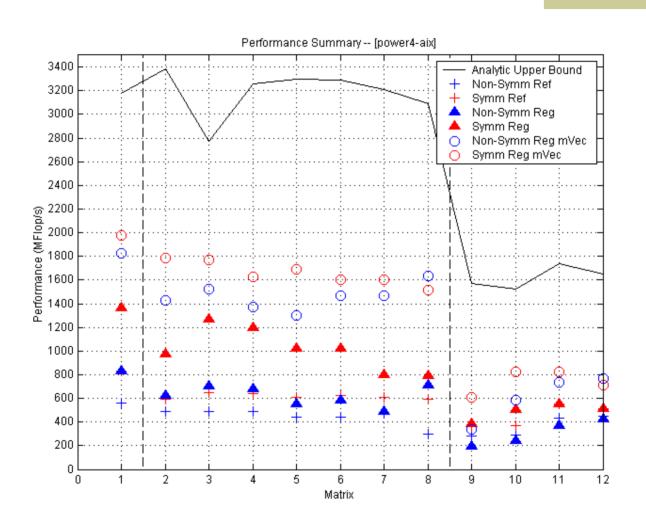
Performance Results: Intel Itanium 1



Performance Results: Intel Itanium 2



Performance Results: IBM Power 4



Conclusions

Matrix Symmetry Optimizations

- Symmetric Performance: 2.6x speedup (median: 1.1x)
 - {Symmetric BCSR Multiple Vector} vs. {Non-Symmetric BCSR Multiple Vector}
- Overall Performance: 7.3x speedup (median: 4.15x)
 - {Symmetric BCSR Multiple Vector} vs. {Non-symmetric CSR Single Vector}
- Symmetric Storage: 64.7% savings (median: 56.5%)
- Cumulative performance effects
- Trade-off between optimizations for register usage

Performance Modeling

- Models account for symmetry, register blocking, multiple vectors
- Gap between measured and predicted performance
 - Measured performance is 68% of predicted performance (PAPI)
 - Model refinements are future work

Current & Future Directions

Heuristic Tuning Parameter Selection

- Register block size and vector width chosen independently
- Heuristic to select parameters simultaneously

Automatic Code Generation

- Automatic tuning techniques to explore larger optimization spaces
- Parameterized code generators

Related Optimizations

- Symmetry (Structural, Skew, Hermitian, Skew Hermitian)
- Cache Blocking
- Field Interlacing

Appendices

Related Work

Automatic Tuning Systems and Code Generation

- PHiPAC [BACD97], ATLAS [WPD01], SPARSITY[Im00]
- FFTW [FJ98], SPIRAL[PSVM01], UHFFT[MMJ00]
- MPI collective ops (Vadhiyar, et al. [VFD01])
- Sparse compilers (Bik [BW99], Bernoulli [Sto97])

Sparse Performance Modeling and Tuning

- Temam and Jalby [TJ92]
- Toledo [Tol97], White and Sadayappan [WS97], Pinar [PH99]
- Navarro [NGLPJ96], Heras [HPDR99], Fraguela [FDZ99]
- Gropp, et al. [GKKS99], Geus [GR99]

Sparse Kernel Interfaces

- Sparse BLAS Standard [BCD+01]
- NIST SparseBLAS [RP96], SPARSKIT [Saa94], PSBLAS [FC00]
- PETSc

Symmetric Register Blocking

Square Diagonal Blocking

- Adaptation of register blocking for symmetry
- Register blocks -r x c
 - Aligned to the right edge of the matrix
- Diagonal blocks -rxr
 - Elements below the diagonal are not included in diagonal block
- Degenerate blocks -rxc'
 - c' < c and c' depends on the block row
 - Inserted as necessary to align register blocks



Register Blocks – 2 x 3

Diagonal Blocks – 2 x 2

Degenerate Blocks - Variable

Multiple Vectors Dispatch Algorithm

Dispatch Algorithm

- k vectors are processed in groups of the vector width (v)
 - SpMM kernel contains v subroutines: SR_i for $1 \le i \le v$
 - SR_i unrolls the multiplication of each matrix element by i
- Dispatch algorithm, assuming vector width v
 - Invoke SR_v floor(k/v) times
 - Invoke $SR_{k\%v}$ once, if k%v > 0

References (1/3)

[GR99]

[BACD97] J. Bilmes, K. Asanovi´c, C.W. Chin, and J. Demmel. Optimizing matrix multiply using PHiPAC; a portable, high-performance, ANSI C coding methodology. In Proceedings of the International Conference on Supercomputing, Vienna, Austria, July 1997. ACM SIGARC. see http://www.icsi.berkelev.edu/.bilmes/phipac. [BCD+01] S. Blackford, G. Corliss, J. Demmel, J. Dongarra, I. Duff, S. Hammarling, G. Henry, M. Heroux, C. Hu, W. Kahan, L. Kaufman, B. Kearfott, F. Krogh, X. Li, Z. Maany, A. Petitet, R. Pozo, K. Remington, W. Walster, C. Whaley, and J. Wolff von Gudenberg. Document for the Basic Linear Algebra Subprograms (BLAS) standard: BLAS Technical Forum, 2001. www.netlib.org/blast. [BW99] Aart J. C. Bik and Harry A. G. Wijshoff. Automatic nonzero structure analysis. SIAM Journal on Computing, 28(5):1576,1587, 1999. [FC00] Salvatore Filippone and Michele Colajanni. PSBLAS: A library for parallel linear algebra computation on sparse matrices. ACM Transactions on Mathematical Software, 26(4):527.550, December 2000. [FDZ99] Basilio B. Fraguela, Ram´on Doallo, and Emilio L. Zapata. Memory hierarchy performance prediction for sparse blocked algorithms. Parallel Processing Letters. 9(3). March 1999. [FJ98] Matteo Frigo and Stephen Johnson. FFTW: An adaptive software architecture for the FFT. In Proceedings of the International Conference on Acoustics. Speech, and Signal Processing, Seattle, Washington, May 1998. [GKKS99] William D. Gropp, D. K. Kasushik, David E. Keyes, and Barry F. Smith. Towards realistic bounds for implicit CFD codes. In Proceedings of Parallel Computational Fluid Dynamics, pages 241.248, 1999.

(ParCo), pages 308.315. Imperial College Press, 1999.

Roman Geus and S. R⁻ ollin. Towards a fast parallel sparse matrix-vector multiplication. In E. H. D'Hollander, J. R. Joubert, F. J. Peters, and H. Sips, editors, *Proceedings of the International Conference on Parallel Computing*

References (2/3)

[TJ92]

[HPDR99] Dora Blanco Heras, Vicente Blanco Perez, Jose Carlos Cabaleiro Dominguez, and Francisco F. Rivera, Modeling and improving locality for irregular problems: sparse matrix-vector product on cache memories as a case study. In HPCN Europe, pages 201.210, 1999. [lm00] Eun-Jin Im. Optimizing the performance of sparse matrix-vector multiplication. PhD thesis, University of California, Berkeley, May 2000. [MMJ00] Dragan Mirkovic, Rishad Mahasoom, and Lennart Johnsson. An adaptive software library for fast fourier transforms. In Proceedings of the International Conference on Supercomputing, pages 215,224. Sante Fe. NM. May 2000. [NGLPJ96] J. J. Navarro, E. Garc´ia, J. L. Larriba-Pey, and T. Juan. Algorithms for sparse matrix computations on high-performance workstations. In Proceedings of the 10th ACM International Conference on Supercomputing, pages 301.308, Philadelpha, PA, USA, May 1996. Ali Pinar and Michael Heath. Improving performance of sparse matrix vector [PH99] multiplication. In Proceedings of Supercomputing, 1999. Markus Puschel, Bryan Singer, Manuela Veloso, and Jose M. F. Moura. Fast [PSVM01] automatic generation of DSP algorithms. In Proceedings of the International Conference on Computational Science, volume 2073 of LNCS, pages 97.106, San Francisco, CA, May 2001. Springer. [RP96] K. Remington and R. Pozo. NIST Sparse BLAS: User's Guide. Technical report, NIST, 1996. gams.nist.gov/spblas. [Saa94] Yousef Saad. SPARSKIT: A basic toolkit for sparse matrix computations, 1994. www.cs.umn.edu/Research/arpa/SPARSKIT/sparskit.html. [Sto97] Paul Stodghill. A Relational Approach to the Automatic Generation of Sequential Sparse Matrix Codes. PhD thesis. Cornell University, August 1997.

In Proceedings of Supercomputing '92, 1992.

O. Temam and W. Jalby. Characterizing the behavior of sparse algorithms on caches.

References (3/3)

[Tol97] Sivan Toledo. Improving memory-system performance of sparse matrix vector

multiplication. In Proceedings of the 8th SIAM Conference on Parallel

Processing for Scientific Computing, March 1997.

[VFD01] Sathish S. Vadhiyar, Graham E. Fagg, and Jack J. Dongarra. Towards an accurate

model for collective communications. In *Proceedings of the International Conference on Computational Science*, volume 2073 of *LNCS*, pages 41.50, San Francisco, CA,

May 2001. Springer.

[WPD01] R. Clint Whaley, Antoine Petitet, and Jack Dongarra. Automated empirical

optimizations of software and the ATLAS project. Parallel Computing,

27(1):3.25, 2001.

[WS97] James B. White and P. Sadayappan. On improving the performance of

sparse matrix-vector multiplication. In Proceedings of the International Conference on

High-Performance Computing, 1997.