Reducing Memory Access Latencies using Data Compression in Sparse, Iterative Linear Solvers All-College Thesis Defense

Neil Lindquist

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Motivation

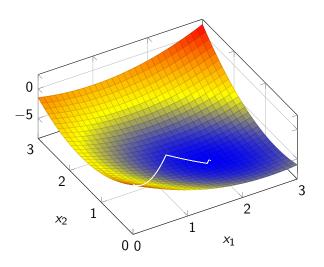
- Sparse systems of linear equations used in many computations
- Iterative solvers are used
- Spend most of the time fetching data

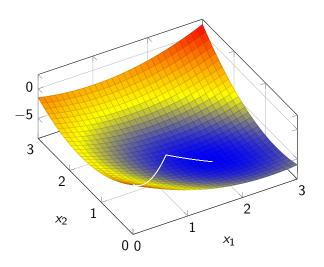
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- If **A** is symmetric, then $\nabla f(\vec{x}) = \mathbf{A}\vec{x} \vec{b}$
- $-\nabla f(\vec{x})$ is in direction of maximal decrease



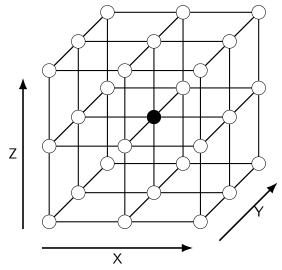


Test Problem

- Approximating the steady state heat equation in 3 dimensions
 - Discretized with a 27-point stencil

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Solver Description

- Preconditioned Conjugate Gradient was used
- 3-level multigrid preconditioner with Symmetric Gauss-Seidel smoother

Compressed Sparse Row Format

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 5 & 8 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 6 & 0 & 4 \end{bmatrix}$$

```
Row 0 1 2 3
Values [1] [5, 8] [3] [6, 4]
Indices [0] [0, 1] [2] [1, 3]
```

Main Data Structures

- 1. Vector Values
- 2. Matrix Values
- 3. Matrix Indices

Compression Methods

- Mixed Floating Point Precision
- SZ Compression
- Elias Gamma and Delta Codings
- ZFP Compression
- Huffman Coding
- Op Code Compression

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Mixed Floating Point Precision

- Two versions of floating point numbers
- Trade off between storage and precision
- Certain vectors can be lower precision without slowing convergence

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- Compression rate is highly dependent on local patterns in the data

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 - Very effective for small integers
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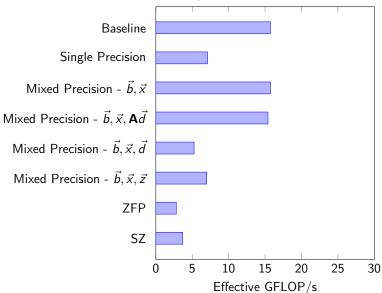
Elias Gamma Coding

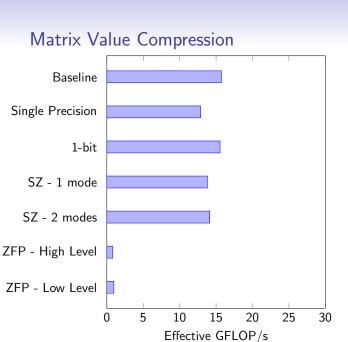
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- For each value, stores the size then the data
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 - Storing the difference from the previous index reduces the size of values
- Elias Delta Coding is similar, but uses Gamma coding for the length
- Compression rate is only dependent on the magnitude of the values

Timing Results

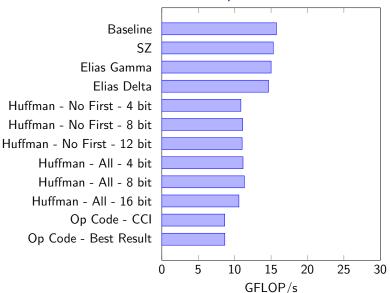
- 60 processes with 96³ rows each
 - 53,084,160 total rows
- A 20-core, 2.2GHz, Intel Broadwell head node
- Plus five 8-core, 1.7GHz Intel Broadwell nodes



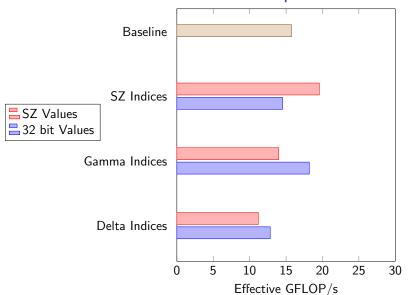




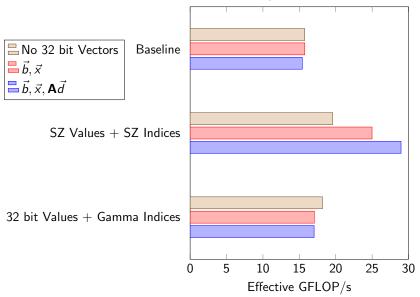
Matrix Index Compression



Matrix Value and Index Compression



Vector and Matrix Compression



Conclusion

- Iterative, sparse linear solvers are memory access bound
- Compressing key data structures provided an 84% increase in performance

Sources

Github.com/Collegeville/HPCG-ZFP