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Application-Based Fault Tolerance Techniques for Fully Protecting Sparse Matrix Solvers

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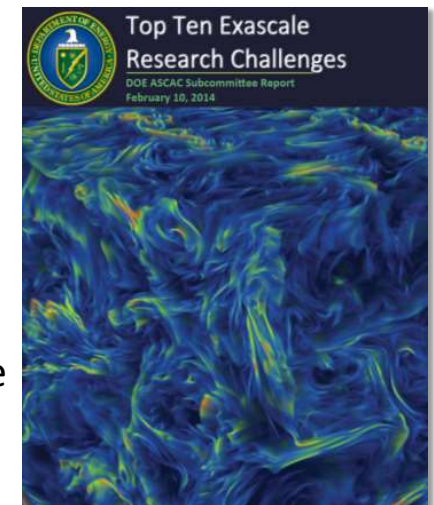
University of Bristol - High Performance Computing Group

<https://uob-hpc.github.io>



Top 10 Exascale challenges

1. **Energy efficiency:** Creating more energy-efficient circuit, power, and cooling technologies.
2. **Interconnect technology:** Increasing the performance and energy efficiency of data movement.
3. **Memory technology:** Integrating advanced memory technologies to improve both capacity and bandwidth.
4. **Scalable system software:** Developing scalable system software that is power- and **resilience-aware**.
5. **Programming systems:** Inventing new programming environments that express massive parallelism, data locality, and **resilience**.
6. **Data management:** Creating data management software that can handle the volume, velocity and diversity of data that is anticipated.
7. **Exascale algorithms:** Reformulating science problems and redesigning, or reinventing, their solution algorithms for exascale systems.
8. **Algorithms for discovery, design, and decision:** Facilitating mathematical optimization and uncertainty quantification for exascale discovery, design, and decision making.
9. **Resilience and correctness** Ensuring correct scientific computation in face of faults, reproducibility, and algorithm verification challenges.
10. **Scientific productivity:** Increasing the productivity of computational scientists with new software engineering tools and environment



February 2014

Why do we need FT?

- Many different kinds of fault can occur during computation (G. Gibson, Proc. of the DSN2006, June, 2006):
 - Soft errors (bit flips in memory etc)
 - Hard errors (component breakage)
 - Power outages
 - OS errors
 - System software errors
- In this work we're interested in the faults which affect the program data

Current Solutions

- Error Correcting Codes implemented in hardware
- Common Codes:
 - Parity (SED)
 - Hamming code - Single Error Correction and Double Error Detection (SECDED)
 - Reed–Solomon code - Chipkill
- ECC does not come for free!
 - Storage overhead
 - Extra energy and bandwidth used
 - Puts restrictions on the hardware that can be used

Error Detecting/Correcting Codes

- Data is stored as **Codewords** in memory
- The codes we are interested in are
 - Parity - 1 extra bit per codeword
 - Hamming Code - Single Error Correction and Double Error Detection (SECDED) with:
 - 64-bit codewords with 8-bits of redundancy
 - 128-bit codewords with 9-bits of redundancy
 - Cyclic Redundancy Check (CRC) Code
 - In particular CRC32C with 32-bits of redundancy per codeword

Application Based Fault Tolerance

- Can take advantage of the data structures and memory access patterns of the application
- User knowledge enables wider range of fault recovery techniques
- A lot of progress being made in:
 - Dense linear algebra
 - Monte Carlo
 - Sparse linear algebra ([this work](#))
 - Spectral (FFT)

ABFT for Sparse Matrix Solvers

- In our research we utilise the TeaLeaf mini-app
 - Part of Sandia National Laboratories' Mantevo (<https://mantevo.org/>) mini-app benchmark suite
- TeaLeaf solves the linear heat conduction equation in 2D on a spatially decomposed regular grid using a five-point stencil
- Vast majority of TeaLeaf's runtime (+98%) is spent performing either matrix-vector products or dot products
- Two main data structures
 - Sparse matrix
 - Dense vectors

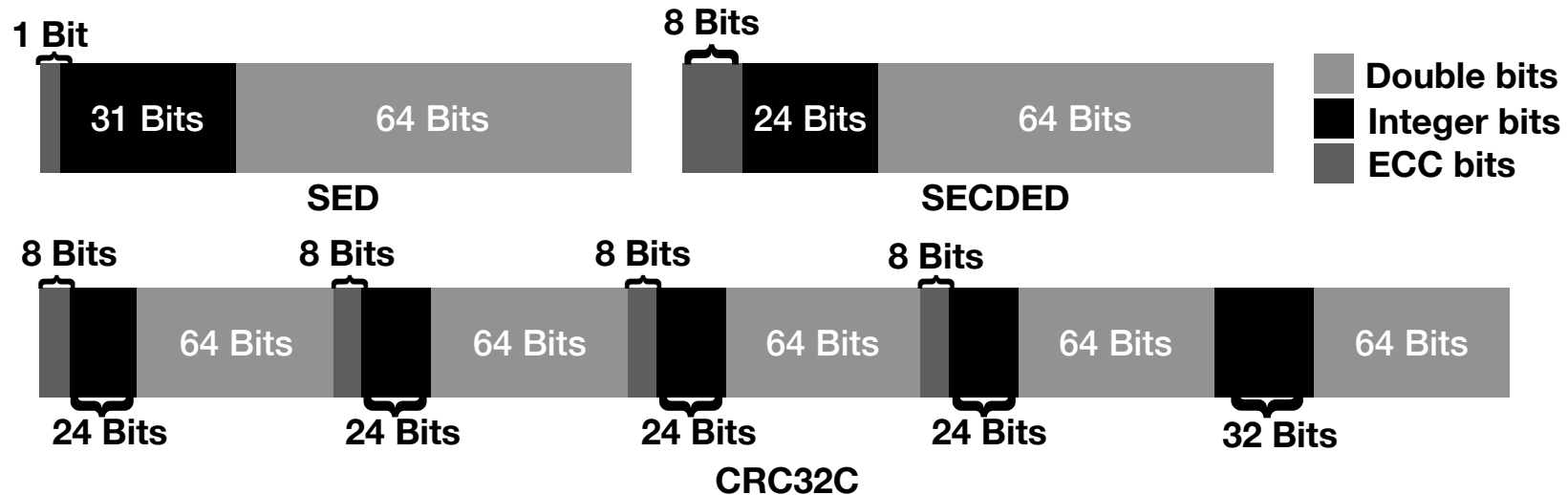
Sparse Matrix Storage

- Most of the matrix elements are zero
- To save space, usually stored in compressed formats
- We focus our efforts on the Compressed Sparse Row (CSR) format where a $m \times n$ matrix is represented by three dense vectors:
 - Vector \mathbf{v} stores the corresponding nonzero values
 - Vector \mathbf{c} stores the column indices for each non-zero value
 - Vector \mathbf{r} stores the offsets of the first nonzero element in each row

ABFT with no storage overhead

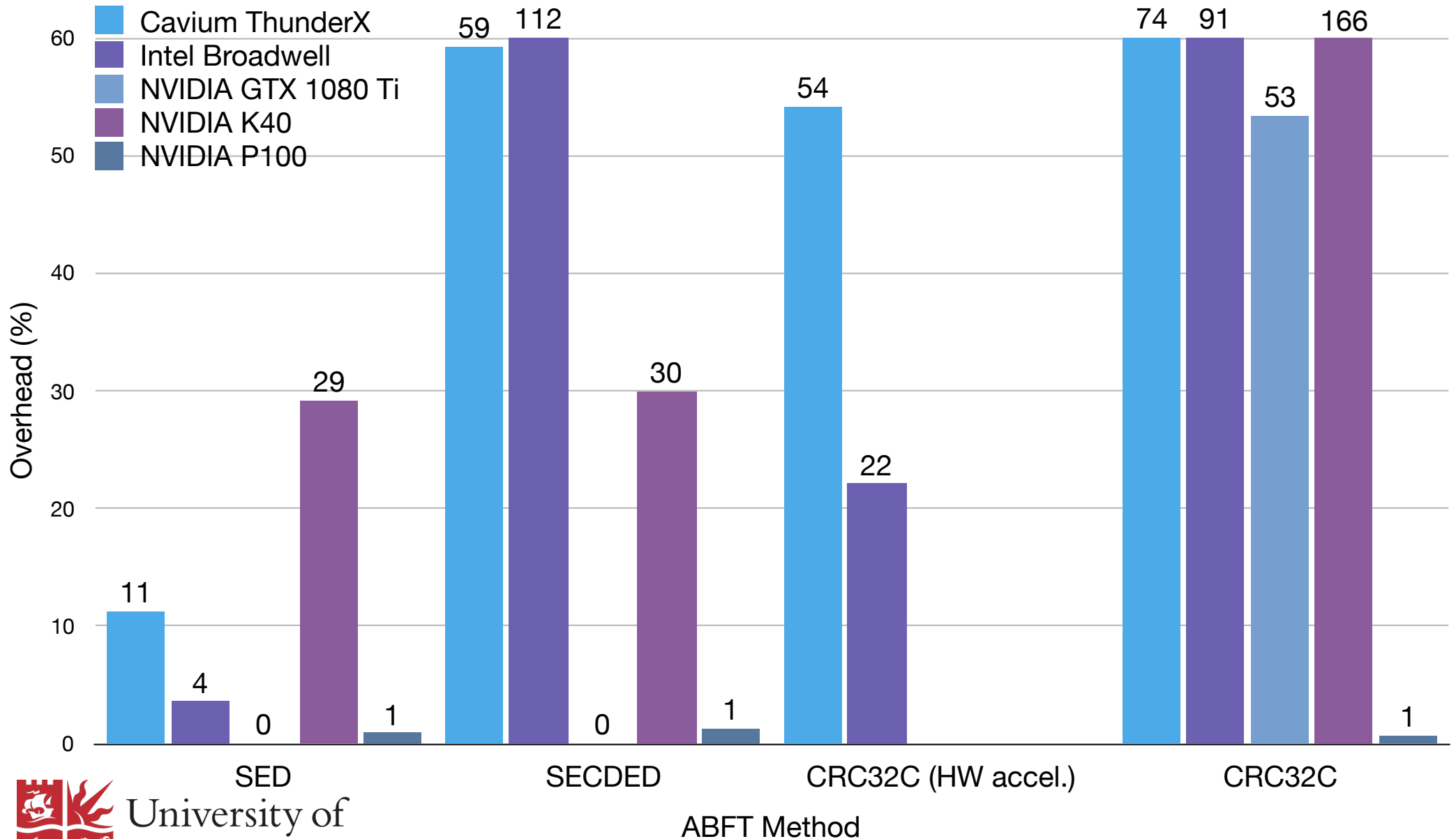
- **Observation 1:** If the matrix has less than $2^{32} - 1$ **columns**, then elements in the column vector **c** will have unused bits
- **Observation 2:** If the matrix has less than $2^{32} - 1$ **nonzero values**, then elements in the row offsets vector **v** will have unused bits
- By further restricting the matrix size we can repurpose these unused bits to store the redundant ECC data
- Note that in many production solvers, the matrix dimensions may not meet our requirements, however:
 - These restrictions apply to a single process
 - Our techniques are easily extended to 64-bit integers

Protecting the CSR Elements

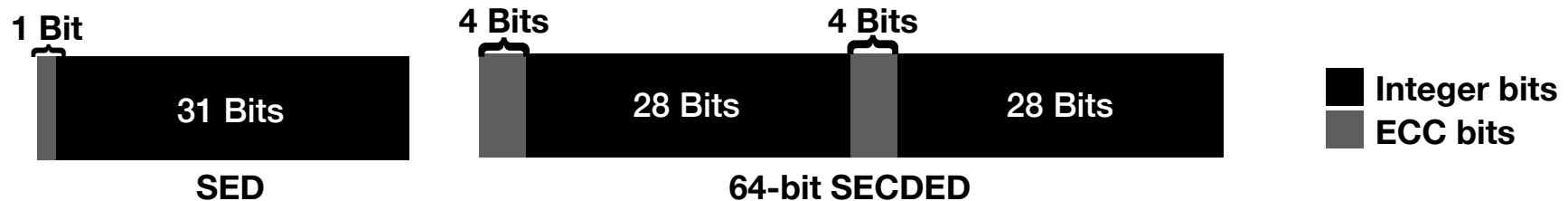


- A CSR element is formed by pairing a nonzero value from vector \mathbf{v} with the corresponding column index from vector \mathbf{c} to form a 96-bit CSR element
- This poses the following limits on the number of columns:
 - SED - maximum $2^{31} - 1$ columns
 - SECDED or CRC32C - maximum $2^{24} - 1$ columns
- When using CRC with a 32-bit checksum, we protect the whole matrix row at a time

Performance Results

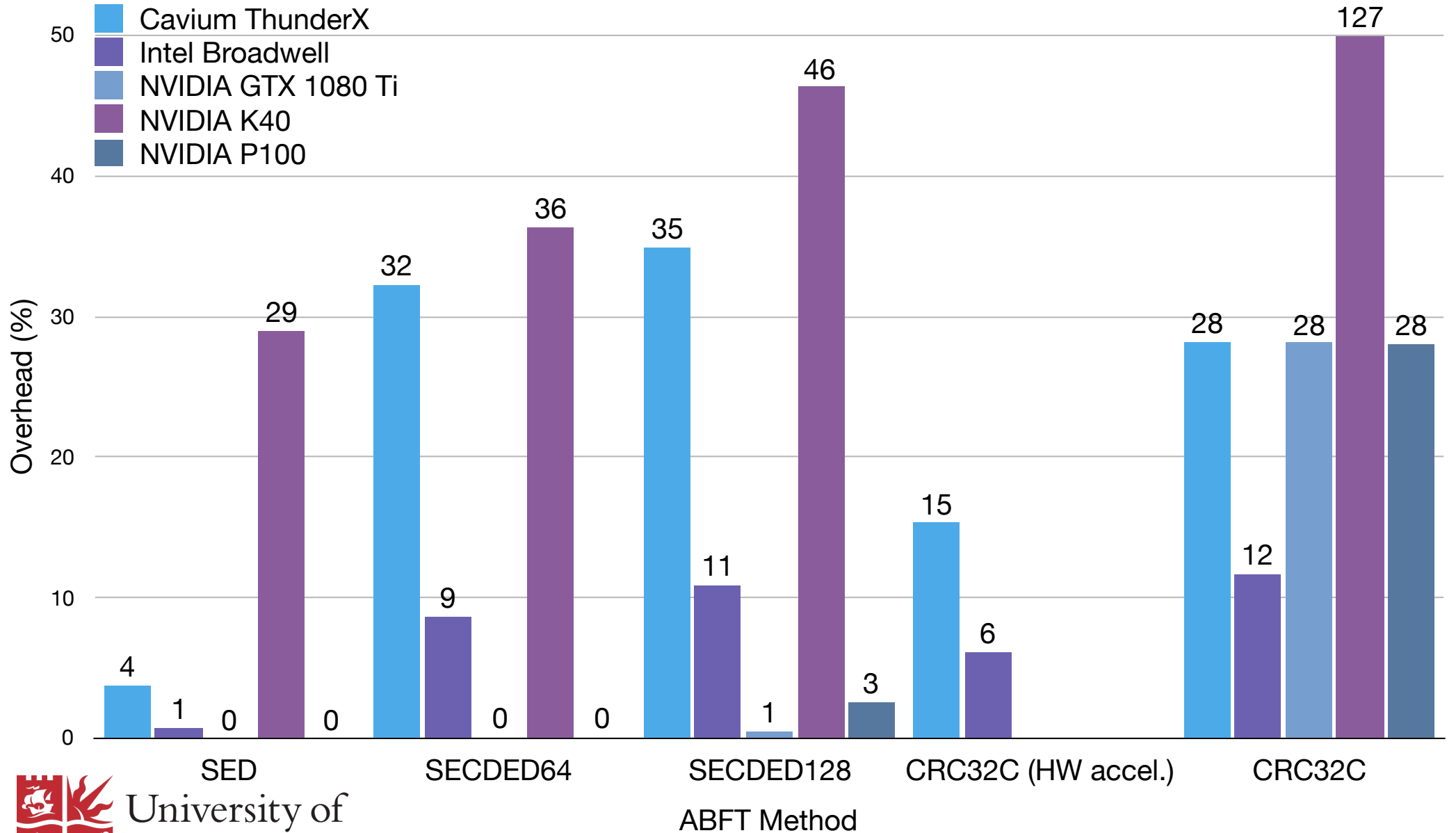


Protecting the Row Offset Vector



- A similar approach for protecting the CSR elements can be applied to protecting the r row offset vector
- When using SED:
 - Matrix can have at most $2^{31} - 1$ nonzero elements.
- In order to use other ECC techniques, we use the top 4 bits from each elements
 - The matrix can still have $2^{28} - 1$ or ≈ 268 million nonzero elements
- Other ECC techniques require more than 4 bits to store the redundancy
 - Protect multiple elements at the same time and split the redundancy bits between multiple elements

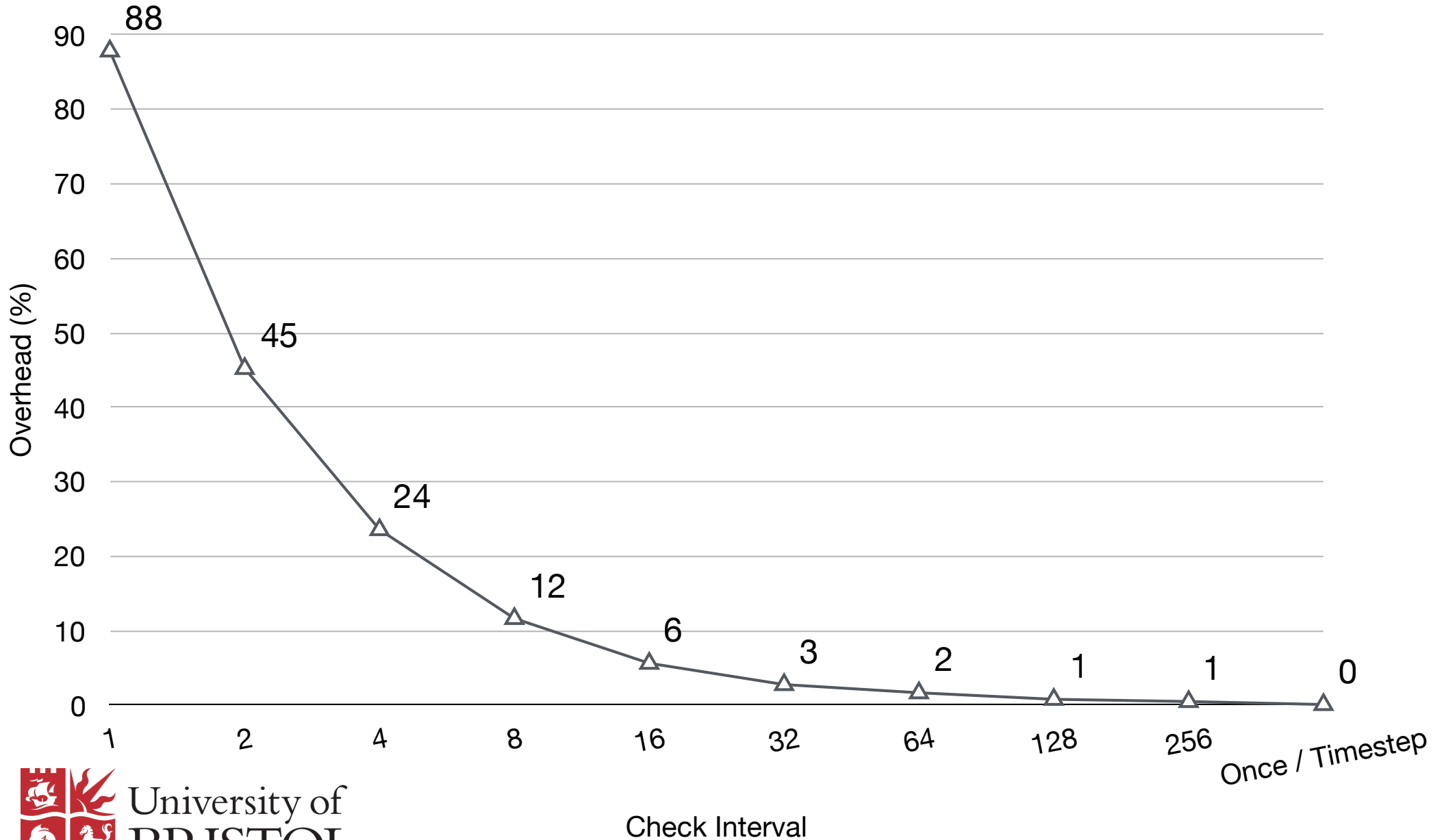
Performance Overheads



Less Frequent Checking

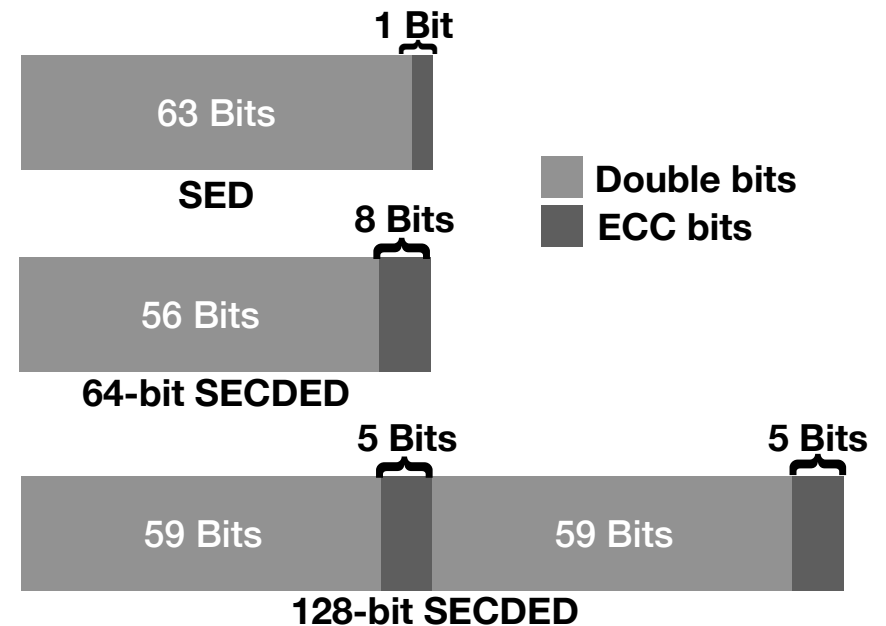
- Observation: During the Conjugate Gradient Solve the matrix does not change
- Perform the matrix integrity checks every N iterations of the algorithm
- Boundary checks on the column and row vector are performed to prevent out of bounds memory access
- Now have to perform up to N more iterations of CG before the error is detected
- We are not able to fully correct any errors, only detect

Performance Results



Floating Point Vector Protection

- Floating point values do not have any unused bits due to their format
- Redundancy bits are stored in the least significant bits of the mantissa
- This storage method poses a risk that the solver may take longer to converge or fail to converge altogether
- The solver has always converged, with the norm of the solution vector within $2.0 \times 10^{-11}\%$ of the expected answer
- Increase in the total number of iterations was less than 1%



Read-Modify-Writes

- Unlike the sparse matrix, the floating point vectors change their values
- When modifying a value in a vector, a Read-Modify-Write (RMW) has to be performed as only part of the codeword is being modified
 - Results in two ECC calculations every write
- Concurrency issues when multiple processes try to write the same ECC codeword

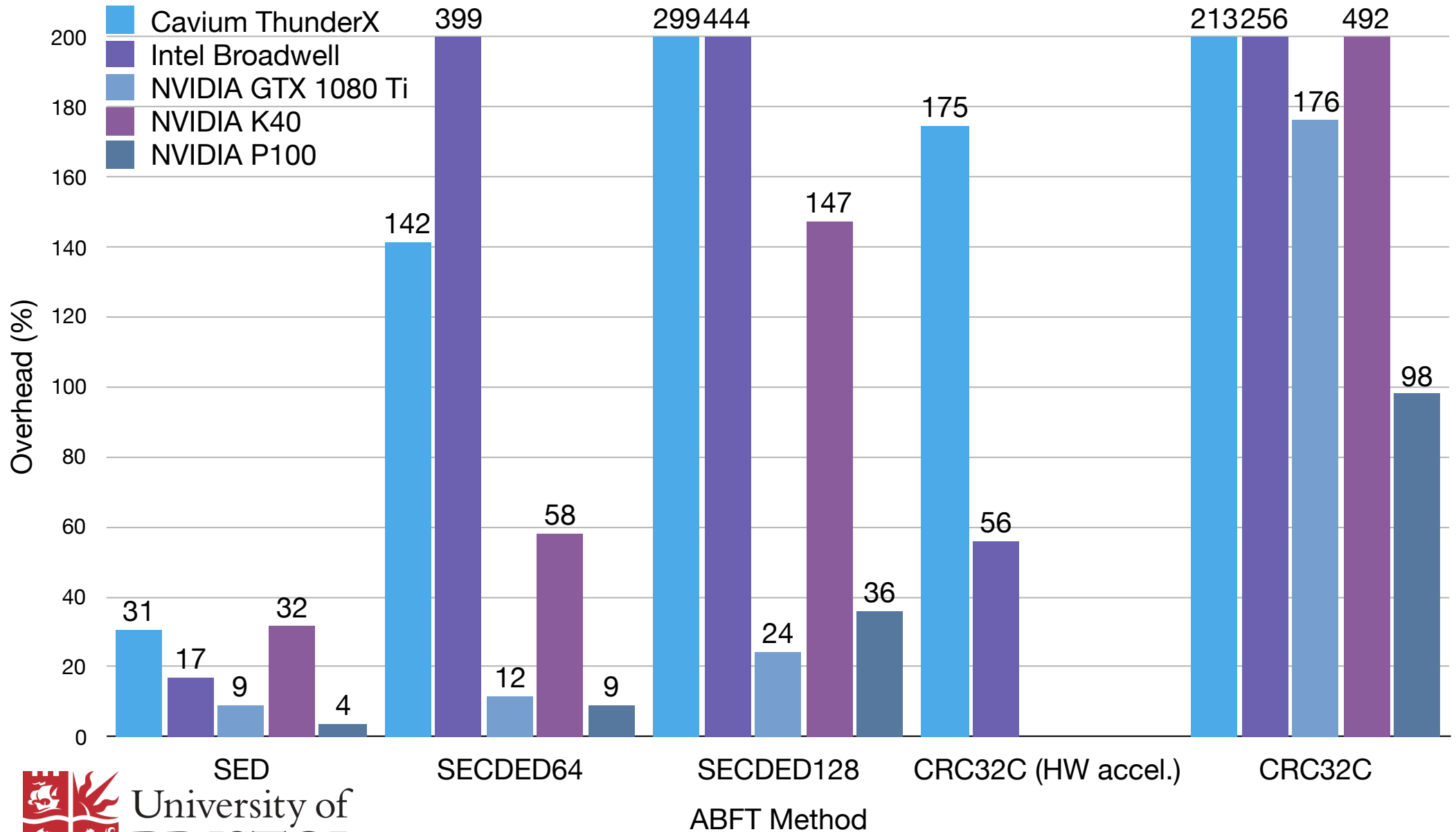
Avoiding RMWs

- **Observation:** When performing calculations at position i , the algorithm will then work on the next element at position $i + 1$
- By buffering the writes a whole ECC element can be committed to memory in one go
 - Single ECC calculation per multiple writes
- The algorithm has to be adapted so that the calculations are performed on the whole ECC element at a time
- Removes the race conditions

Caching

- By buffering ECC elements when performing reads most of duplicate integrity checks can be removed
- This buffering technique performs poorly for the Sparse Matrix - Vector multiplication due to five-point stencil access pattern
 - At least 3 ECC compound elements are accessed per iteration
- By leveraging the knowledge about the application we can create a caching scheme within the kernel that is both multiple ECC element and multi-iteration aware

Performance Results



Conclusions

- Demonstrated efficient ABFT techniques with no storage overhead
- We have shown that hardware accelerated calculations were a big improvement over software-only solutions
 - Instruction set design can help with achieving better performance, and that combining software and hardware methods to protect against errors might prove beneficial.
- Ideally these ABFT techniques would be implemented directly inside of libraries/packages such as **PETSc** or **Trilinos**

References

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Thank you!

Any questions?

