# **Maximal Atomic irRedundant** Sets: a Usage-Based Dataflow **Partitioning Algorithm**

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#### Context of this work

- HPC Applications: Large volumes of data, low number of operations
  - → I/O intensive, low operational intensity
  - Significant intrinsic parallelism
  - « Splitting » the workload between nodes or accelerators
- Communications are extremely expensive (time + energy)
  - GPU / FPGA to host (PCIe): thousands of cycles per transaction
  - MPI (network): millions of cycles per transaction
  - Each transaction = penalty
- Under-utilization of transfer resource = bottleneck

**Need to optimize host-accelerator communications** 



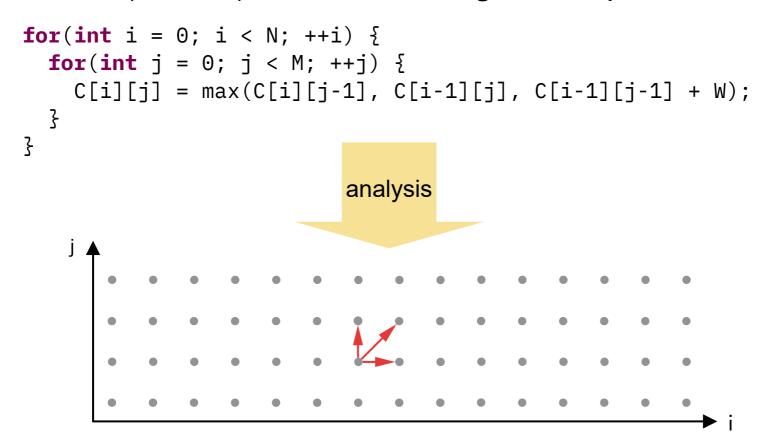




### Programs we target

#### Computational kernels that admit a polyhedral model

Iteration space + dependence function (e.g. from Array Dataflow Analysis [1])



Smith-Waterman kernel iteration space and dependences

[1] Feautrier, P. Dataflow analysis of array and scalar references. International Journal of Parallel Programming, Springer Science and Business Media LLC, 1991, 20, 23-53

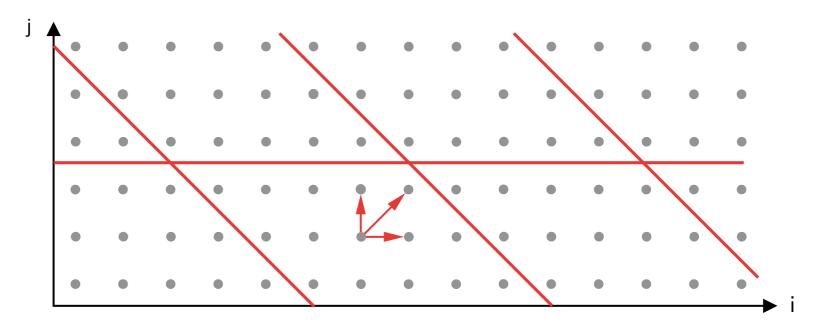






### Benefits of Loop Tiling

- Tiling
  - Already applied, e.g. for temporal locality & parallelism
- Uniform dependences (vectors)
  - Inter-tile communications = same across all tiles



Tiling of Smith-Waterman kernel iteration space

We seek to improve spatial locality as well

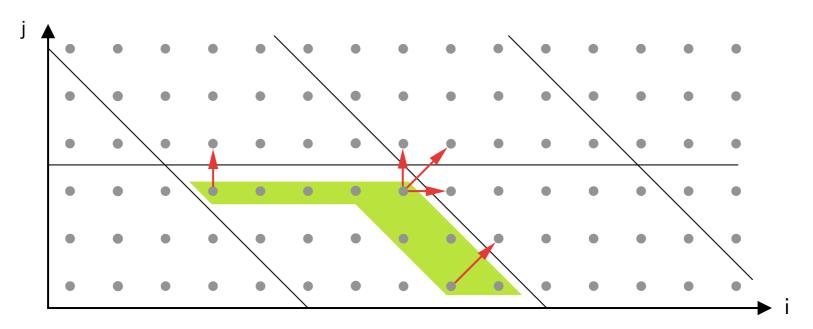






#### Inter-tile communications: flow-in/out

- Intermediate values used by other tiles → communications
- Bondhugula (2013) [2]: communicated sets = flow-in / flow-out sets
- Iterations consumed in another tile = Flow-out



Flow-out set of a tile of iterations with a Smith-Waterman kernel

#### **Each Consumer Tile Needs Parts of Flow-out**

[2] Bondhugula, U. Compiling Affine Loop Nests for Distributed-Memory Parallel Architectures. Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis, ACM, 2013



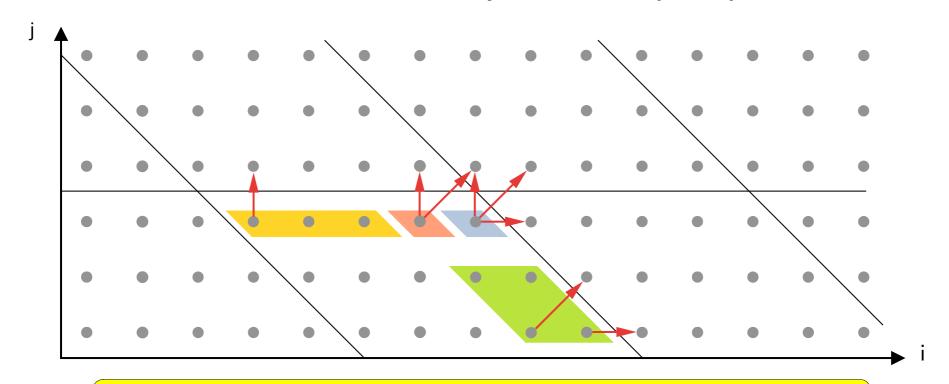






#### **Maximal Atomic irRedundant Sets**

- Single-Producer (SP): all iterations in a MARS come from *one* tile
- All-Consumed (AC): MARS are entirely consumed by every consumer tile



**MARS** guarantee the absence of read + write redundancy







#### State of the Art

- Decomposition of Inter-Tile Communications:
  - Datharthri et al., 2013 [3]: Flow-In/Flow-Out partitioning
    - → MARS = one specific case, static determination at compile time
  - Zhao et al, 2021 [4]: partitioning + layout
    - → MARS = « generalization » to uniform dependences
- Memory Layout for Host-Accelerator Communications:
  - Ozturk et al., 2009 [5]: data tiling + compression
    - → MARS = **finer-grain data breakdown** amenable to compression
- Allocation from a Polyhedral Model:
  - Yuki and Rajopadhye, 2013 [6]: lower memory footprint with Uniform Dependences
    - → MARS = trade footprint for bandwidth utilization

[3] Dathathri, R.; Reddy, C.; Ramashekar, T. & Bondhugula, U. *Generating Efficient Data Movement Code for Heterogeneous Architectures with Distributed-Memory.*Proceedings of the 22nd International Conference on Parallel Architectures and Compilation Techniques, IEEE, 2013

[4] Zhao, T.; Hall, M.; Johansen, H. & Williams, S. *Improving communication by optimizing on-node data movement with data layout* Proceedings of the 26th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming, ACM, 2021

[5] Ozturk, O.; Kandemir, M. & Irwin, M. Using Data Compression for Increasing Memory System Utilization. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, Institute of Electrical and Electronics Engineers (IEEE), 2009, 28, 901-914

[6] Yuki, T. & Rajopadhye, S. Memory allocations for tiled uniform dependence programs IMPACT 2013, 2013, 13







#### Outline

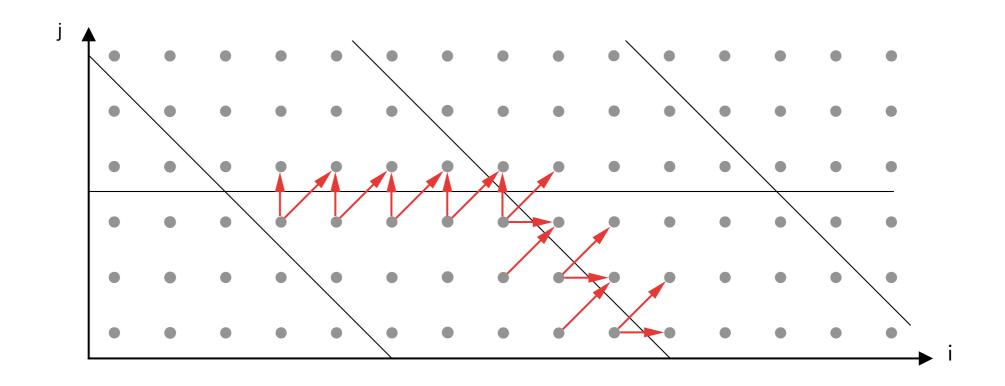
- Construction of MARS
  - Core Notion: « dependence crossing hyperplane »
  - Illustrated Construction
- Implementation results: Examples and Analysis
- Discussion: Possible uses





### Constructing the flow-out

• Inter-tile dependence : some dependence crosses some tiling hyperplane



**Expressible using hyperplane standard equation** 

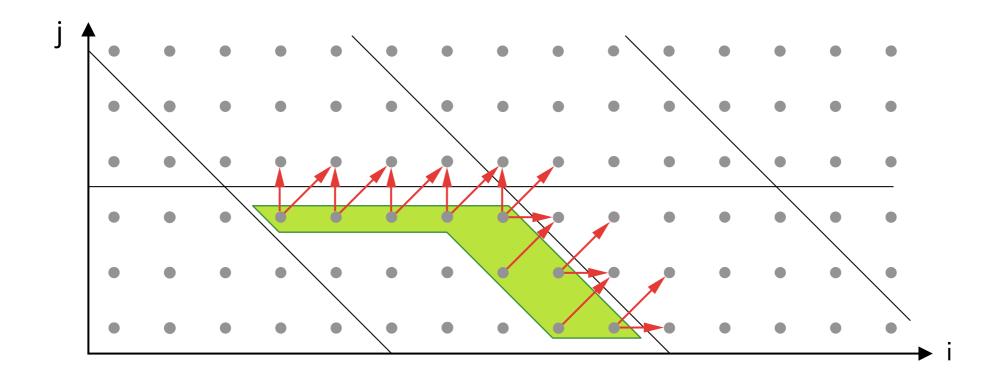






### Constructing the flow-out

• **Flow-out:** *iteration points* such that translating by *some* dependence vector crosses *some* tiling hyperplane

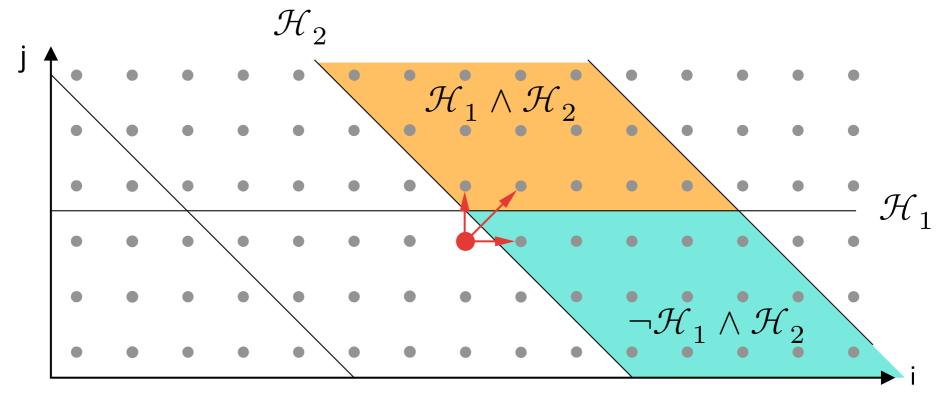






#### Consumer Tiles

- Defined per iteration point
- Some dependence crosses exactly select hyperplanes to consumer tile

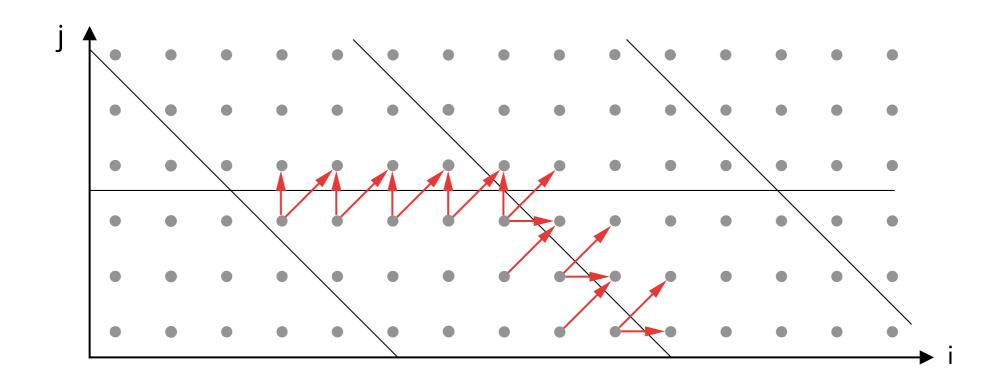


Iteration point in red has 2 consumer tiles





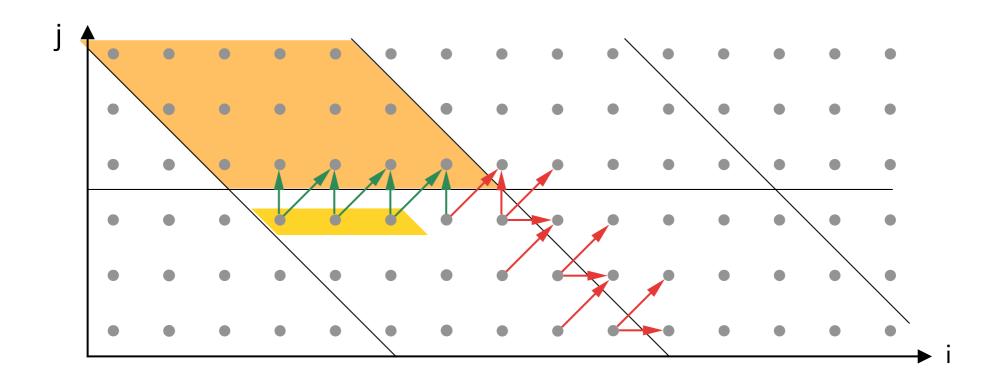






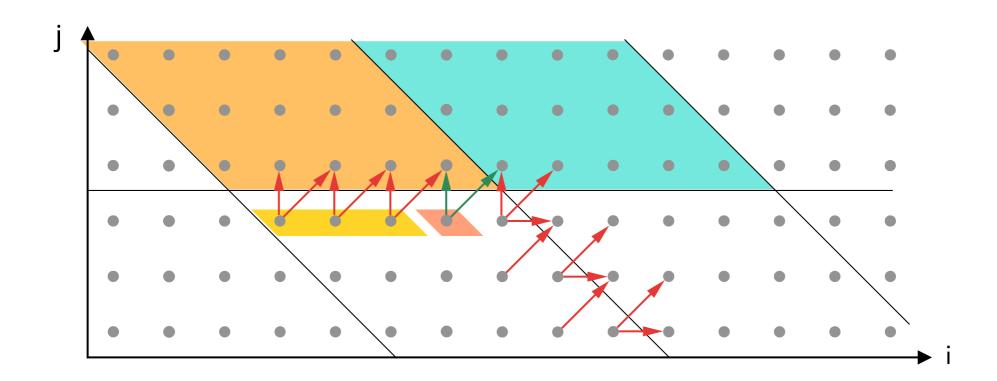








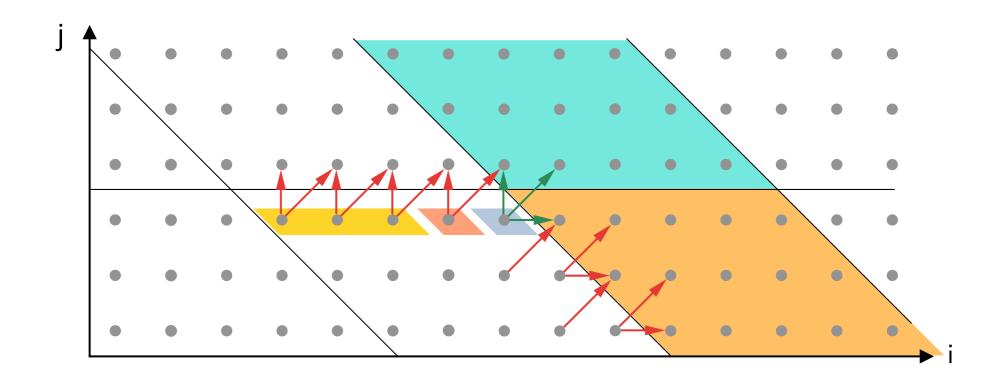






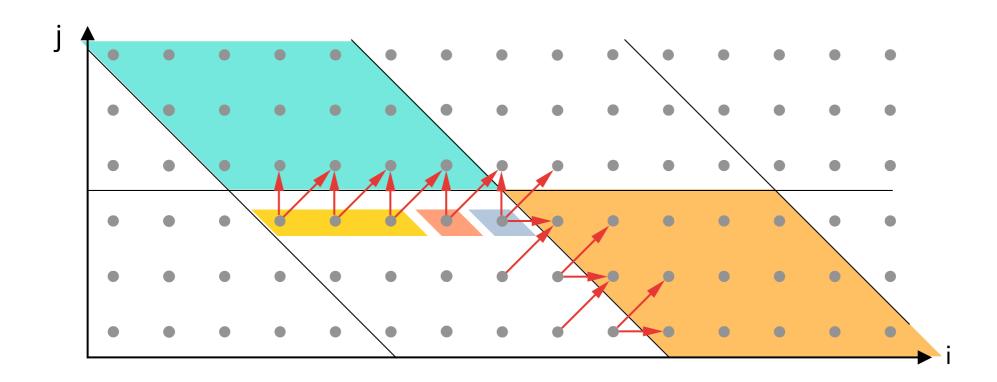








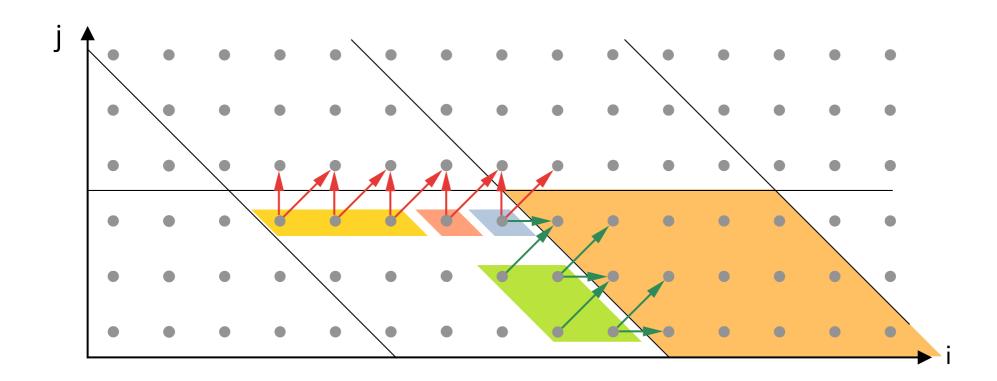










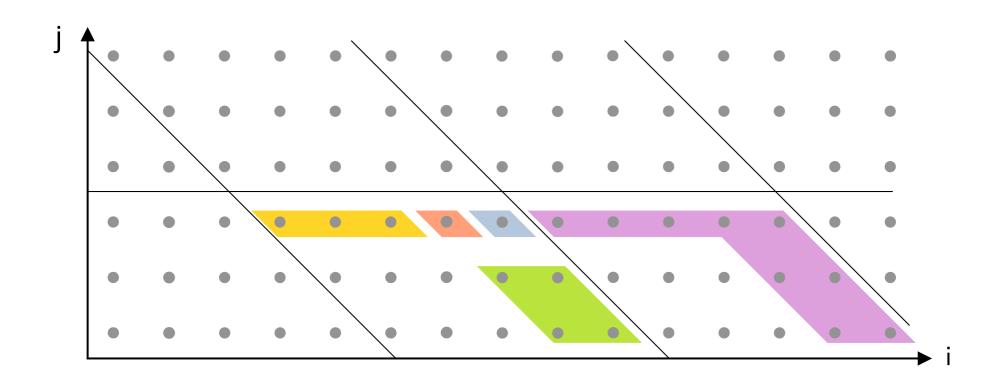








MARS: iterations consumed exclusively by specific consumer tiles



**Union of MARS = Flow-Out** 







### **Computation Performance**

- MARS calculator available online (https://github.com/cferr/mars.git)
  - Jupyter notebook using ISLPy
- Runtime:
  - 1-5 seconds if ≤ 3 tiling hyperplanes
  - **2 hours** for 4 tiling hyperplanes
  - Cause: exhaustive exploration of power set of power set (2^(2^n) elements)
- Recursive implementation : ~10 seconds for 4 tiling hyperplanes
  - Not yet publicly released

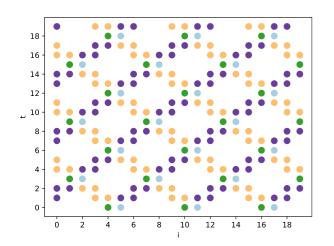
We have alleviated MARS calculation complexity





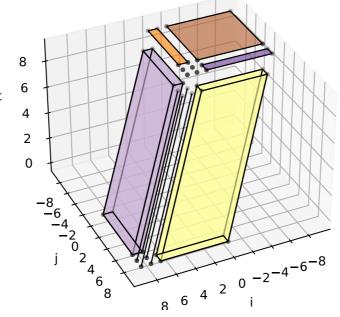


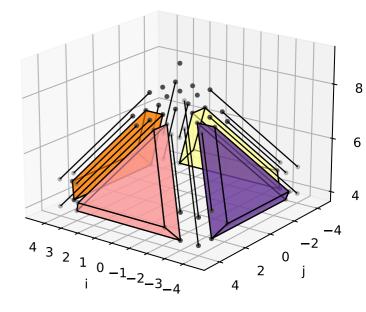
### MARS supports 1D, 2D, 3D spaces...



Jacobi 1D, diamond tiling

Jacobi 2D, skewed tiling





Jacobi 2D, « diamond » tiling

... and non-canonical tiling hyperplanes!





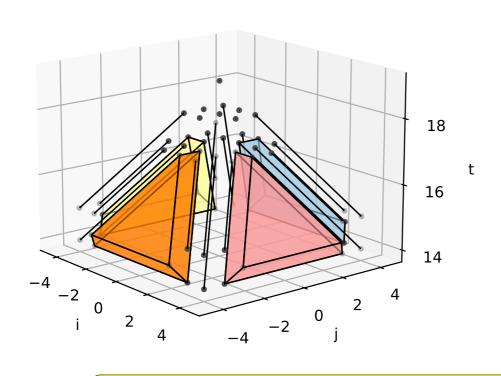


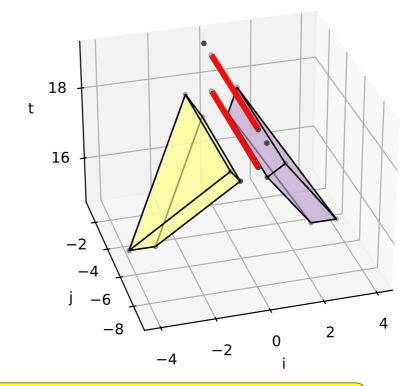
### MARS supports non-LI hyperplanes

- Tiling hyperplanes aren't Linearly Independent (4 hyperplanes for a 3D space)
- Example : Jacobi 2D Diamond, 3 tile shapes

MARS Flow-Out (jacobi2d d): k4 = k1 - k2 + k3

MARS Flow-Out (jacobi2d\_d) : k4 = 1 + k1 - k2 + k3





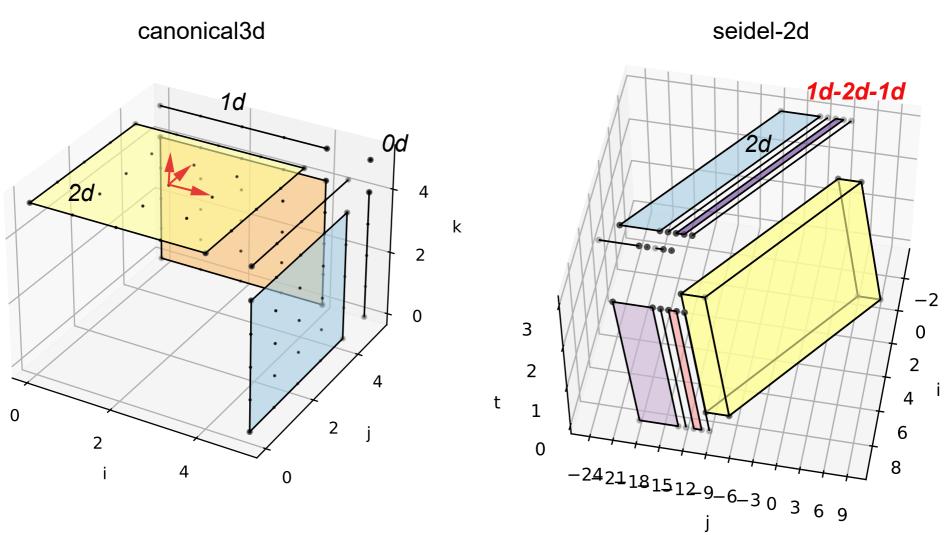
**Each tile shape produces different MARS** 







#### Counterintuitive Observation...



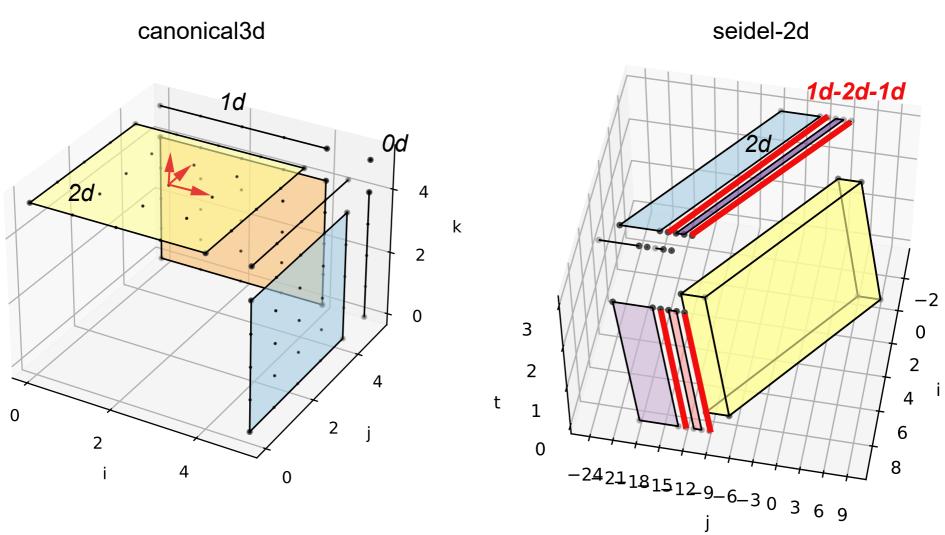
MARS dimensionality does not necessarily decrease as we get closer to intersections of edges







#### Counterintuitive Observation...



MARS dimensionality does not necessarily decrease as we get closer to intersections of edges







### **Applications of MARS**

#### Memory allocation for FPGA accelerators

 Work In Progress: automatically derive a data layout minimizing read transactions

#### Compression

 Along with data layout → increase the effective bandwidth (amount of useful data transmitted over the bus) thanks to MARS' irredundancy

#### Fault tolerance

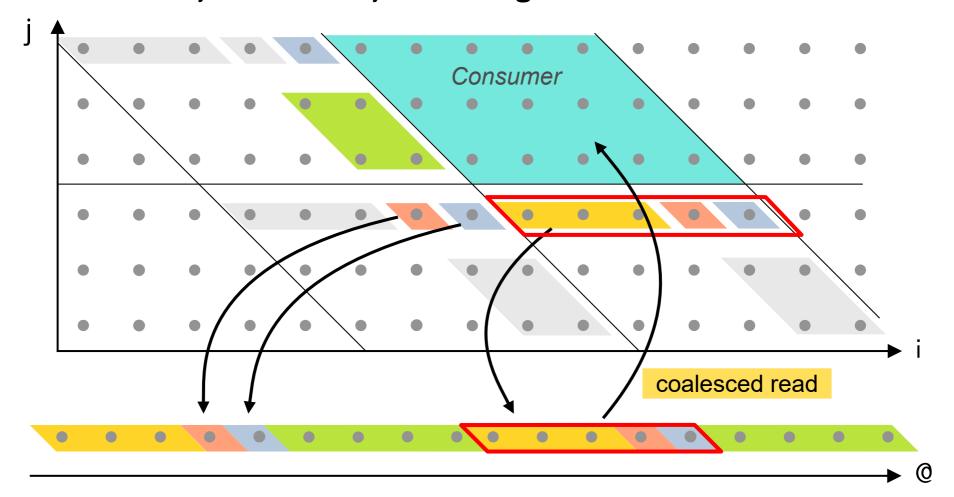
 Compute a checksum on each MARS. If error → the producer tile (known) is to be re-executed.





#### MARS for FPGA-Host communications

Find MARS layout in memory minimizing read time



Formulated as an LP optimization problem - WIP

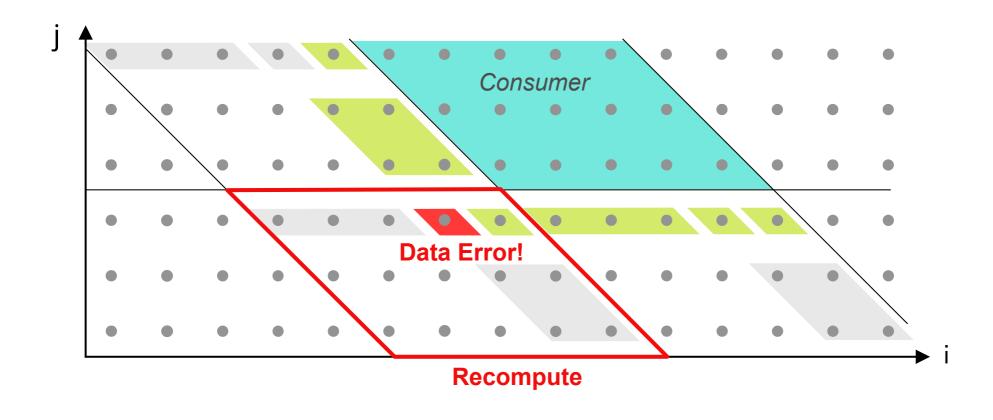






#### MARS for Error Detection

Checksum MARS to determine if data from producer tile has errors



We can use MARS for overclocking, undervolting

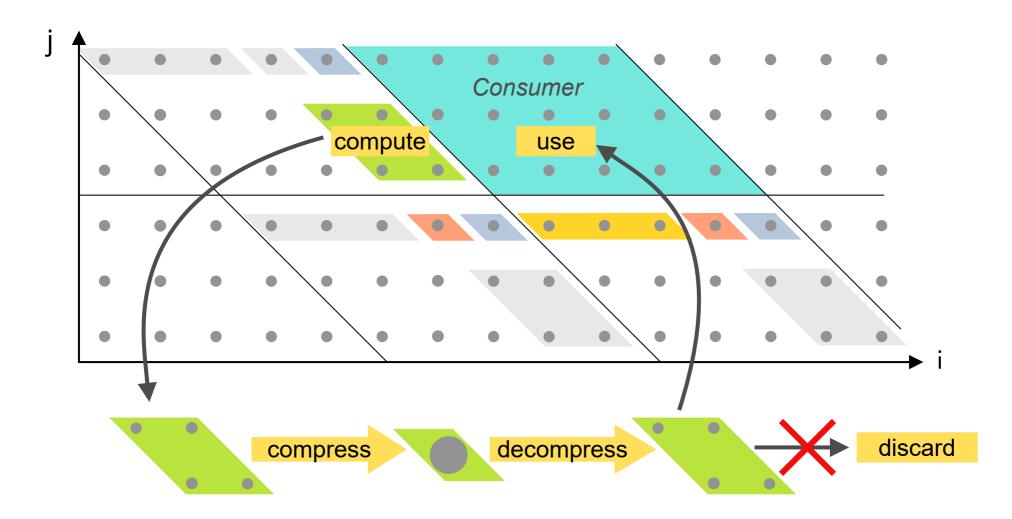






#### MARS for Irredundant Compression

Compression without readback redundancy

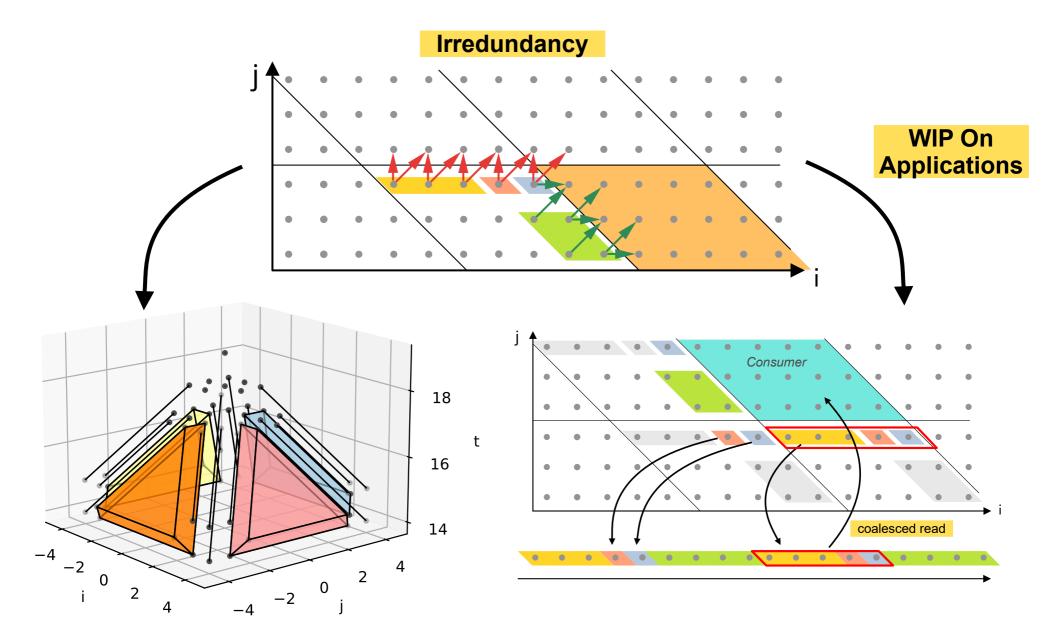








#### Conclusion - Take-Home









## Thank you

Questions?





