NEAR DATA PROCESSING

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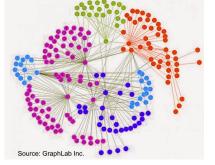


Data Processing Trends

□ Why processing in memory ...

Scaling Limitations Near Data **Processing End of Denard** scaling **New Technologies** 3D stacking,

Emerging Applications



Graph analytics, deep neural nets, etc.

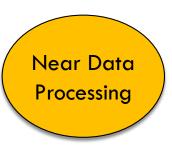
3D stacking, resistive memories, etc.

[ref: GraphLab, ZME]

Requirements for Efficient NDP

Throughput

 High processing throughput to match the high memory bandwidth



Power

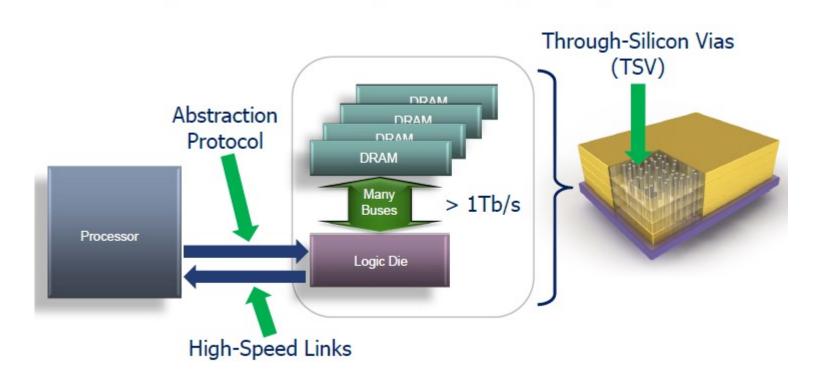
Thermal constraints limit clock frequency

Flexibility

Must amortize manufacturing cost through reuse across apps

Memory Technologies

☐ HMC: hybrid memory cube



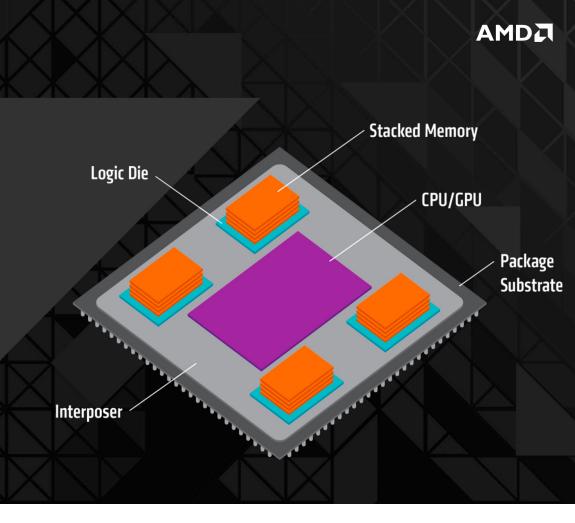
Notes: Tb/s = Terabits / second HMC height is exaggerated

[ref: micron]

High Bandwidth Memory

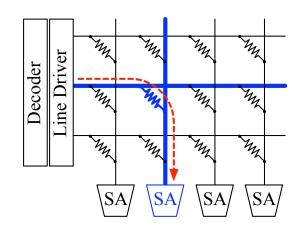
THE INTERPOSER THE NEXT STEP IN INTEGRATION

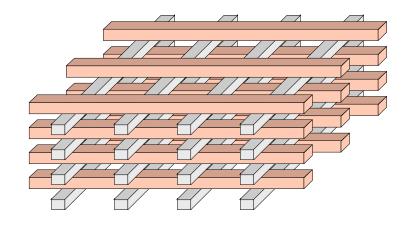
- Brings DRAM as close as possible to the logic die
- Improving proximity enables extremely wide bus widths
- Improving proximity simplifies communication and clocking
- Improving proximity greatly improves bandwidth per watt
- Allows for integration of disparate technologies such as DRAM
- AMD developed industry partnerships with ASE, Amkor & UMC to develop the first high-volume manufacturable interposer solution



Resistive Memory Technology

- □ 3D crosspoint promises virtually unlimited memory
 - Non-volatile
 - 10x higher density
 - Main limit for now 6GB/sec interface

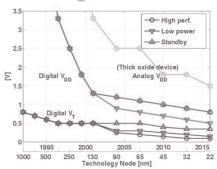




Near Data Processing

How to map applications to NDP technology?

Scaling Limitations



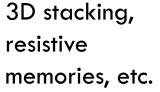
End of Denard scaling



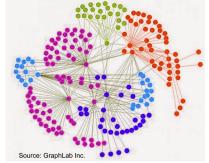




New Technologies



Emerging Applications

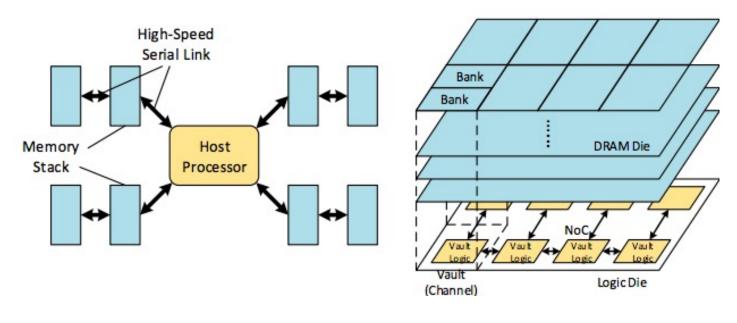


Graph analytics, deep neural nets, etc.

[ref: GraphLab, ZME]

Near Data Processing

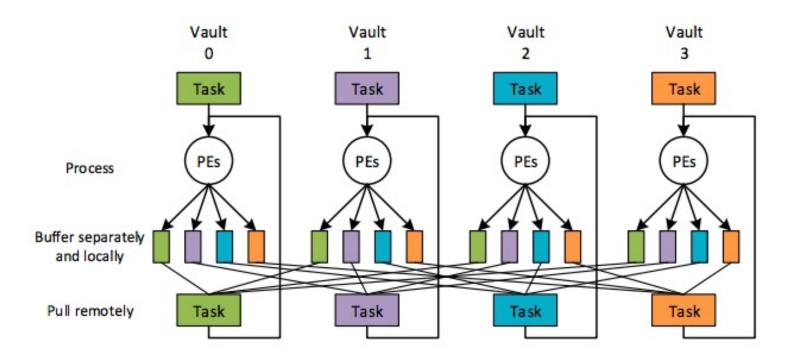
- Example
 - Stacks run memory intensive code
 - Multiple stacks linked to host processor (SerDes)



HMC

Design Challenges

- Communication within and across stacks
 - Fine-grained vs. coarse-grained blocks



Efficient NDP Architecture

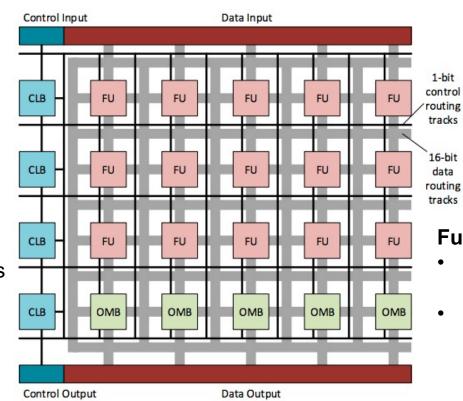
- □ Flexibility, area and power efficiency
- □ HRL: heterogeneous reconfigurable logic

Configurable Logic Block

- LUTs for embedded control logic
- Special functions: sigmoid, tanh, etc.

Output MUX Block

- Configurable MUXes (tree, cascading, parallel)
- Put close to output, low cost and flexible



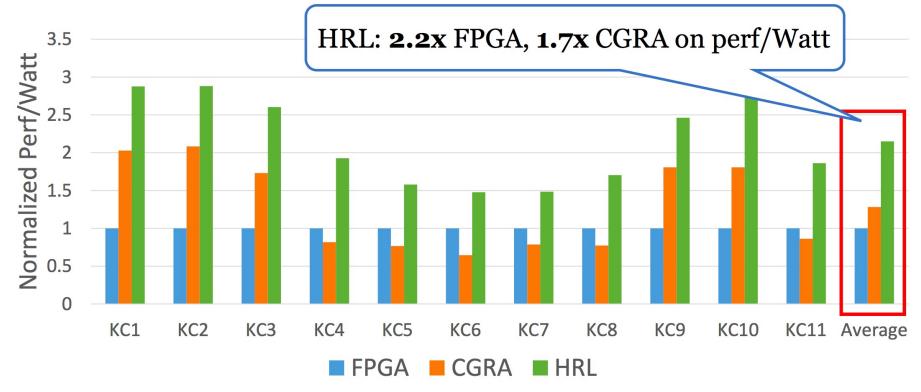
Functional Unit

- Efficient 48-bit arithmetic/logic ops
- Registers for pipelining and retiming

[HPCA'16]

Power Efficiency

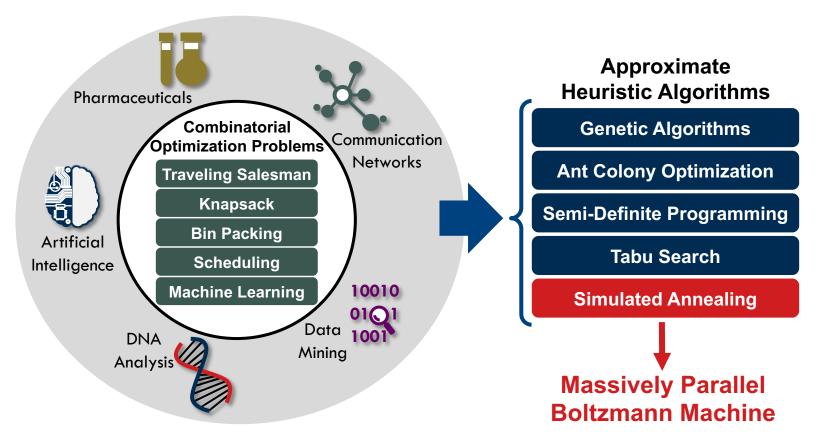
- 2.2x performance/Watt over FPGA
- Within 92% of ASIC performance



[HPCA'16]

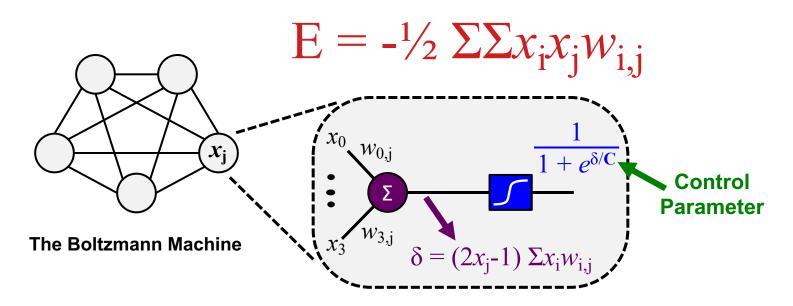
Combinatorial Optimization

 Numerous critical problems in science and engineering can be cast within the combinatorial optimization framework.



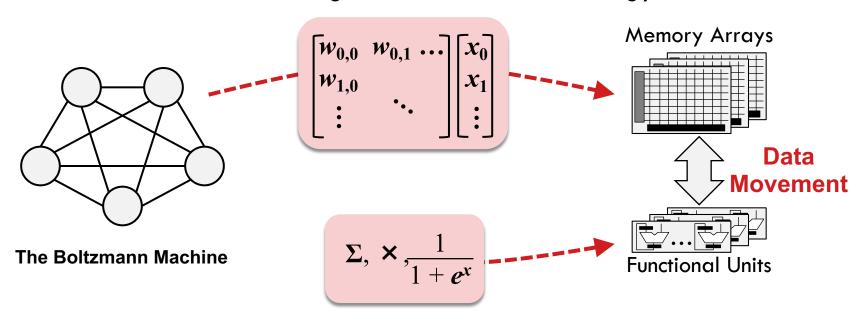
The Boltzmann Machine

- Two-state units connected with real-valued edge weights form a stochastic neural network.
- Goal: iteratively update the state or weight variables to minimize the network energy (E).



Computational Model

- Network energy is minimized by adjusting either the edge weights or recomputing the states.
- Iterative matrix-vector multiplication between weights and states is critical to finding minimal network energy.

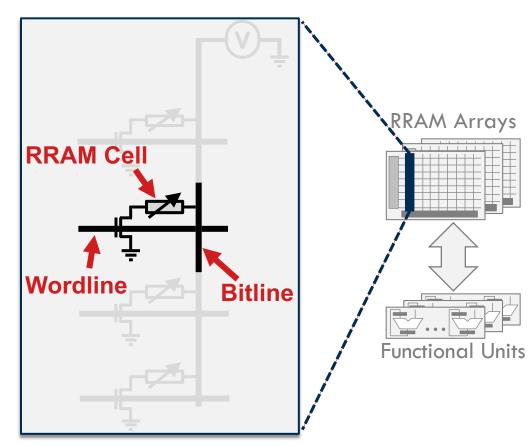


Resistive Random Access Memory

 An RRAM cell comprises an access transistor and a resistive switching medium.



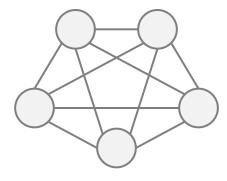
RRAM: Resistive RAM (source: HP, 2009)



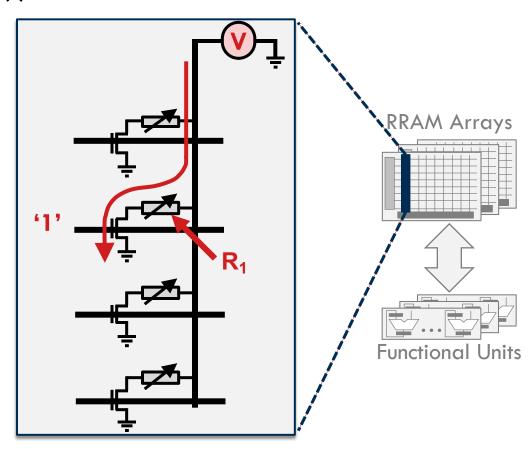
Resistive Random Access Memory

 A read is performed by activating a wordline and measuring the bitline current (I).

$$I = V/R_1$$



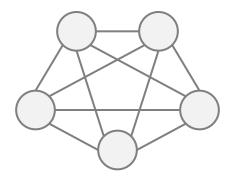
The Boltzmann Machine



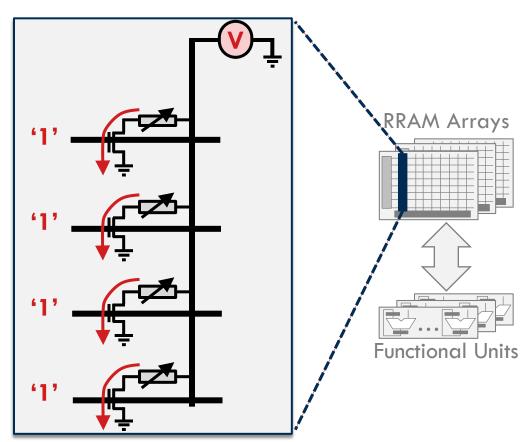
Memristive Boltzmann Machine

 Key Idea: exploit current summation on the RRAM bitlines to compute dot product.

$$I = \Sigma V/R_i$$

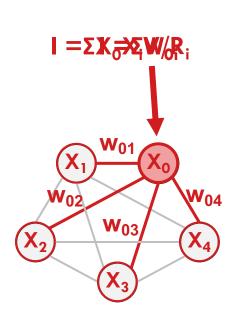


The Boltzmann Machine

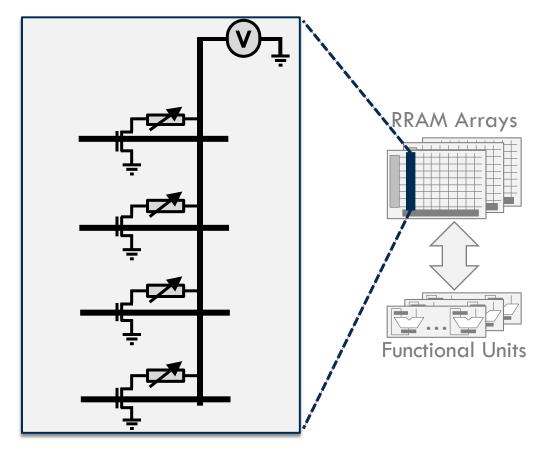


Memristive Boltzmann Machine

 Memory cells represent the weights and state variables are used to control the bitline and wordlines.

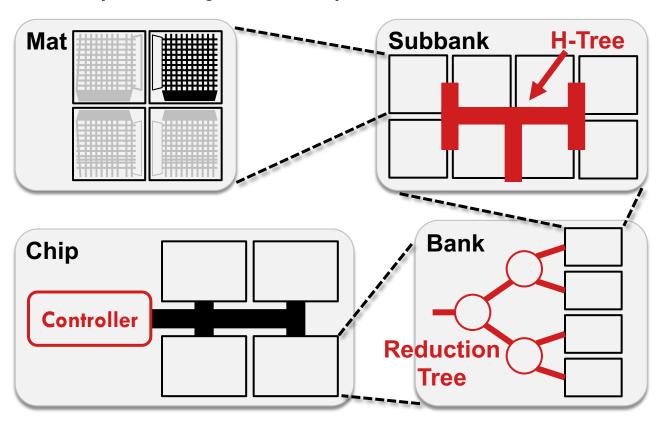


The Boltzmann Machine



Chip Organization

 Hierarchical organization with configurable reduction tree is used to compute large sum of product.



Software configures the on-chip data layout and initiates the optimization by writing to a memory mapped control register.

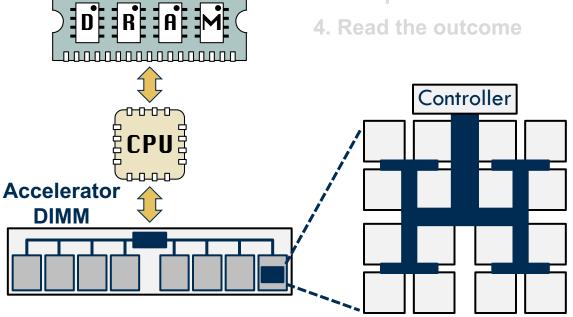
To maintain ordering, accesses to the accelerator are made uncacheable by the processor.

DDR3 reads and writes are used for configuration and data transfer.



2. Write weights and states

3. Compute



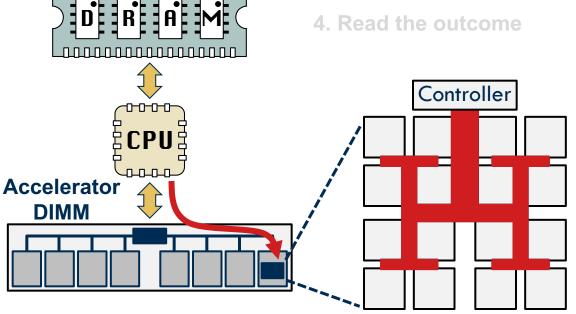
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1. Configure the DIMM

- 2. Write weights and states
- 3. Compute



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and data transfer. 1. Configure the DIMM 2. Write weights and states Model $(m \times n)$ 3. Compute 4. Read the outcome Controller **Accelerator** DIMM

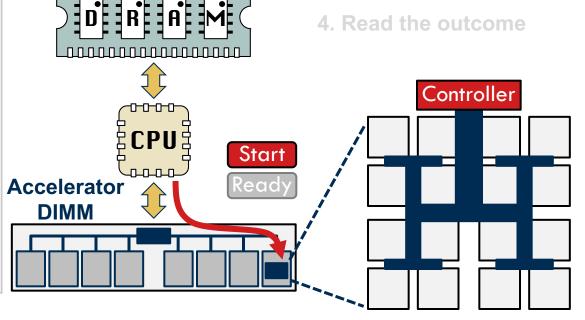
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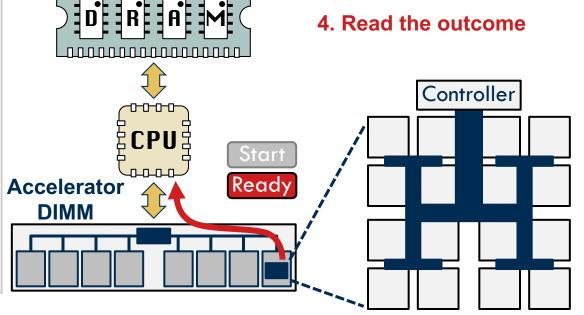
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Summary of Results

