# **Advanced Technology Opportunities**

#### **ISCA Tutorial (2017)**

Website: <a href="http://eyeriss.mit.edu/tutorial.html">http://eyeriss.mit.edu/tutorial.html</a>



# **Advanced Storage Technology**

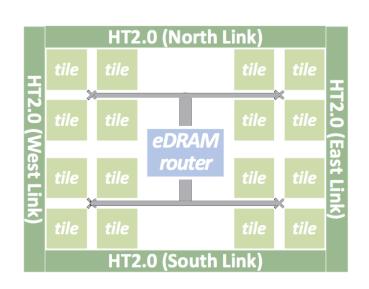
- Embedded DRAM (eDRAM)
  - Increase on-chip storage capacity
- 3D Stacked DRAM
  - e.g. Hybrid Memory Cube Memory (HMC), High Bandwidth Memory (HBM)
  - Increase memory bandwidth

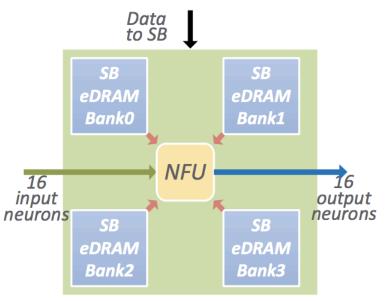


# eDRAM (DaDianNao)

- Advantages of eDRAM
  - 2.85x higher density than SRAM
  - 321x more energy-efficient than DRAM (DDR3)
- Store weights in eDRAM (36MB)
  - Target fully connected layers since dominated by weights

16 Parallel Tiles

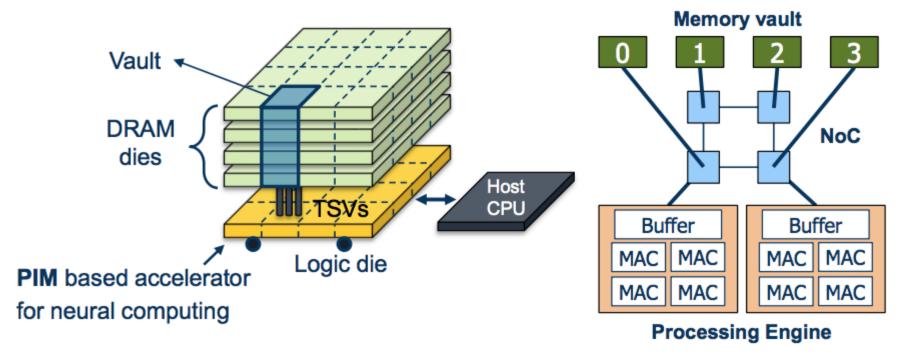






# Stacked DRAM (NeuroCube)

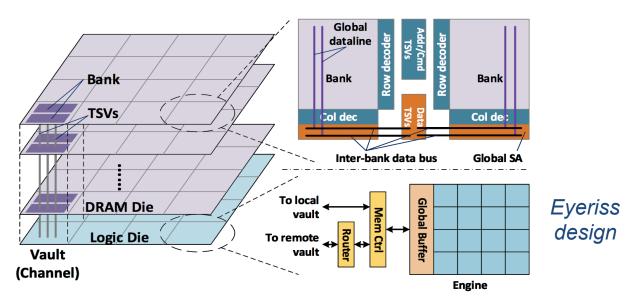
- NeuroCube on Hyper Memory Cube Logic Die
  - 6.25x higher BW than DDR3
    - HMC (16 ch x 10GB/s) > DDR3 BW (2 ch x 12.8GB/s)
  - Computation closer to memory (reduce energy)





# Stacked DRAM (TETRIS)

- Explores the use of HMC with the Eyeriss spatial architecture and row stationary dataflow
- Allocates more area to the computation (PE array) than on-chip memory (global buffer) to exploit the low energy and high throughput properties of the HMC
  - 1.5x energy reduction, 4.1x higher throughput vs. 2-D DRAM





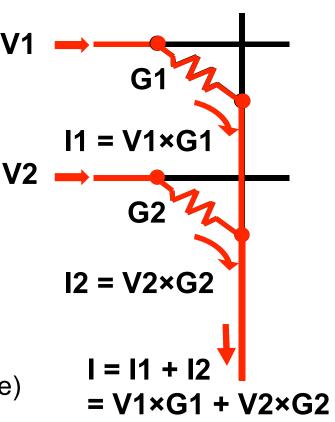
# **Analog Computation**

- Conductance = Weight
- Voltage = Input
- Current = Voltage × Conductance
- Sum currents for addition

$$Output = \sum Weight \times Input$$

Input = V1, V2, ...

Filter Weights = G1, G2, ... (conductance)



#### Weight Stationary Dataflow



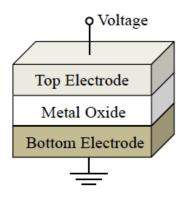
# **Memristor Computation**

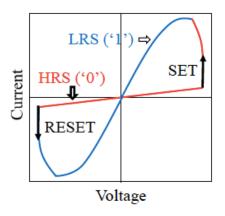
# Use memristors as programmable weights (resistance)

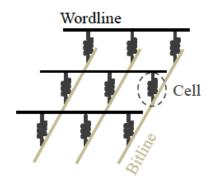
- Advantages
  - High Density (< 10nm x 10nm size\*)</li>
    - ~30x smaller than SRAM\*\*
    - 1.5x smaller than DRAM\*\*
  - Non-Volatile
  - Operates at low voltage
  - Computation within memory (in situ)
    - Reduce data movement



#### **Memristor**





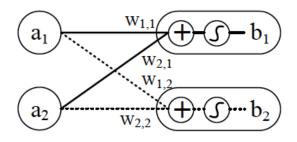


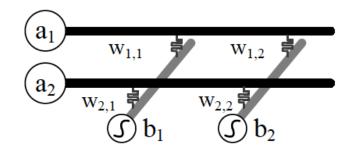
(a) Conceptual view of a ReRAM cell

(b) I-V curve of bipolar switching

(c) schematic view of a crossbar architecture

$$b_j = \sigma(\sum_{\forall i} a_i \cdot w_{i,j})$$





- (a) An ANN with one input and one output layer
- (b) using a ReRAM crossbar array for neural computation



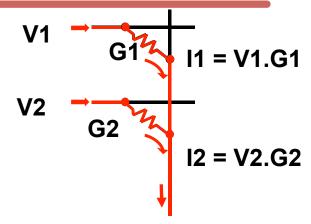
### **Challenges with Memristors**

- Limited Precision
- A/D and D/A Conversion
- Array Size and Routing
  - Wire dominates energy for array size of 1k × 1k
  - IR drop along wire can degrade read accuracy
- Write/programming energy
  - Multiple pulses can be costly
- Variations & Yield
  - Device-to-device, cycle-to-cycle
  - Non-linear conductance across range

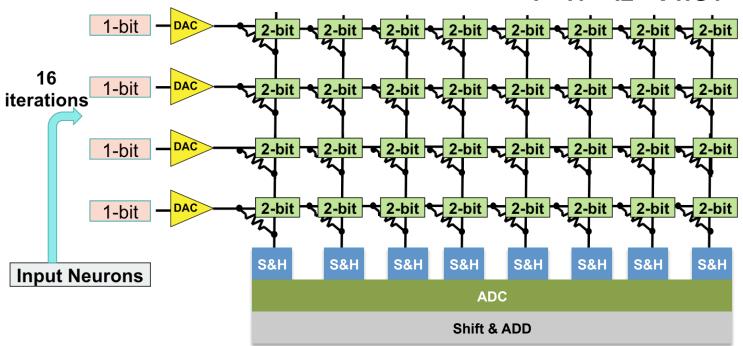


#### **ISAAC**

- eDRAM using memristors
- 16-bit dot-product operation
  - 8 x 2-bits per memristors
  - 1-bit per cycle computation

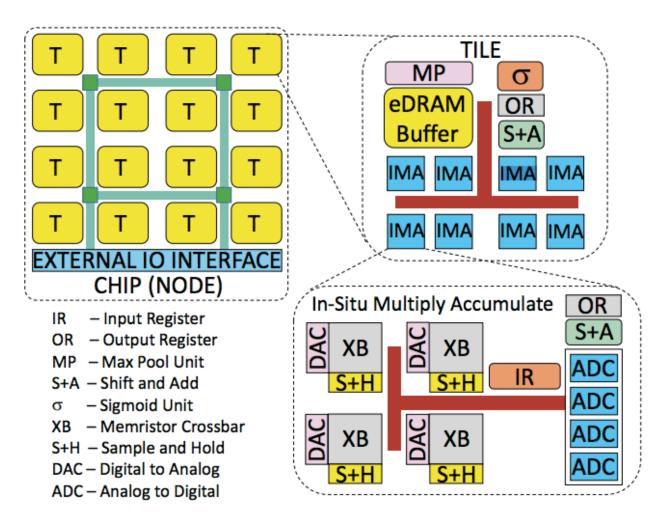


I = I1 + I2 =V1.G1 + V2.G2





#### **ISAAC**



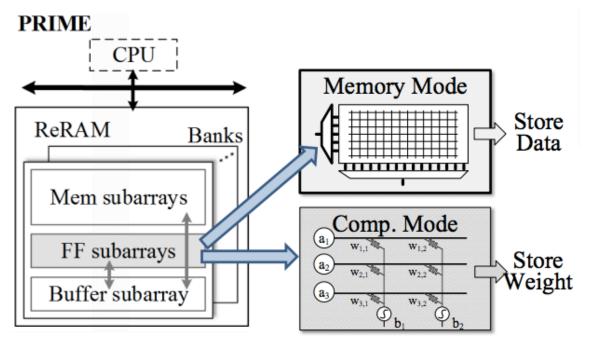
Eight 128x128 arrays per IMA

12 IMAs per Tile



#### **PRIME**

- Bit precision for each 256x256 ReRAM array
  - 3-bit input, 4-bit weight (2x for 6-bit input and 8-bit weight)
  - Dynamic fixed point (6-bit output)
- Reconfigurable to be main memory or accelerator
  - 4-bit MLC computation; 1-bit SLC for storage

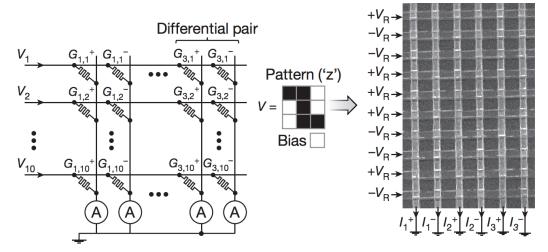


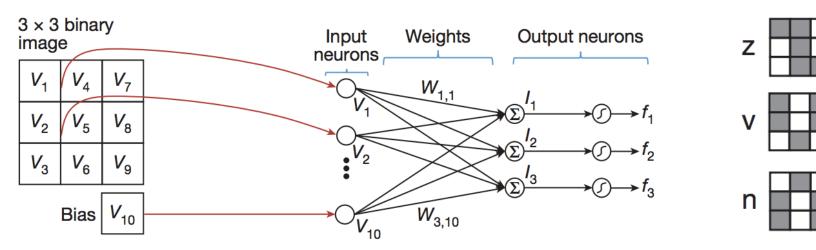


#### **Fabricated Memristor Crossbar**

# Transistor-free metal-oxide 12x12 crossbar

- A single-layer perceptron (linear classification)
- 3x3 binary image
- 10 inputs x 3 outputs x 2 differential weights = 60 memristors







# **Optical Neural Network**

#### Matrix Multiplication in the Optical Domain

The photodetection rate is 100 GHz

"In principle, such a system can be at least two orders of magnitude faster than electronic neural networks (which are restricted to a GHz clock rate)"

