

Breaking the memory-wall for AI: In-memory compute, HBMs or both?

Presented By: Kailash Prasad

PhD Electrical Engineering

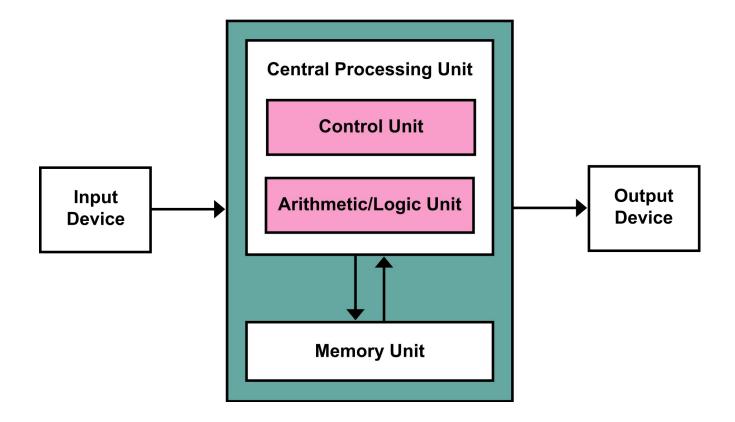
Outline



- Motivation
- HBM High Bandwidth Memory
- IMC In Memory Computing
- In-memory compute, HBMs or both?
- Conclusion

Von - Neumann Architecture

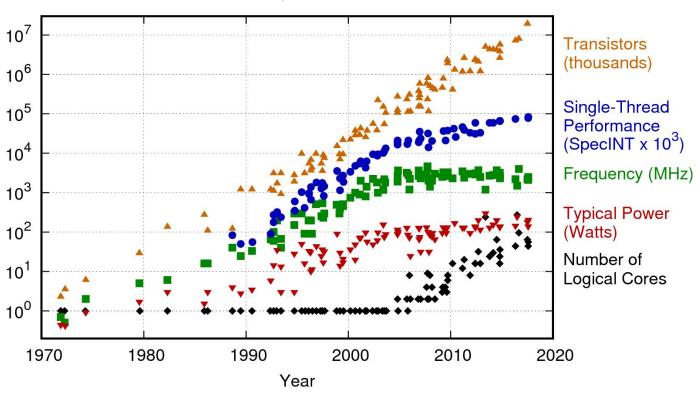




Moore's Law



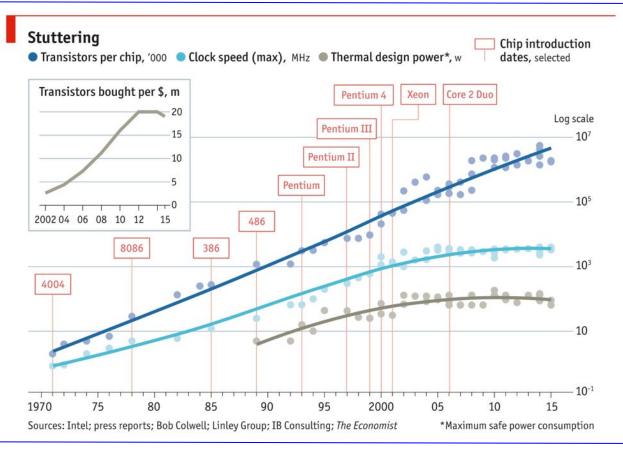
42 Years of Microprocessor Trend Data



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten New plot and data collected for 2010-2017 by K. Rupp

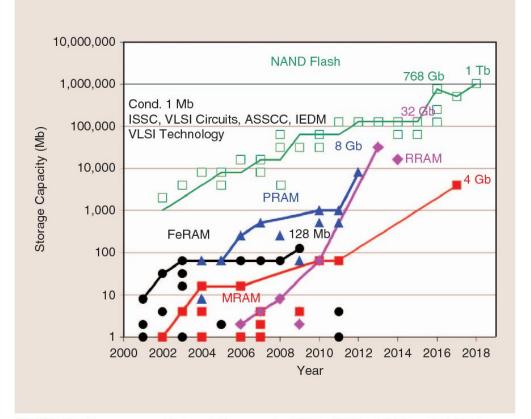
Power Wall





Hwang's Law





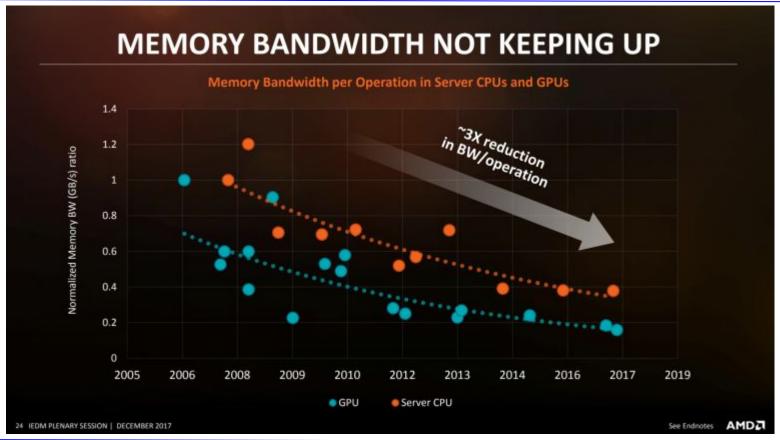


Hwang's Law: Chip capacity will double every year

FIGURE 30: Memory-capacity trends for emerging NVMs. ASSCC: IEEE Asian Solid-State

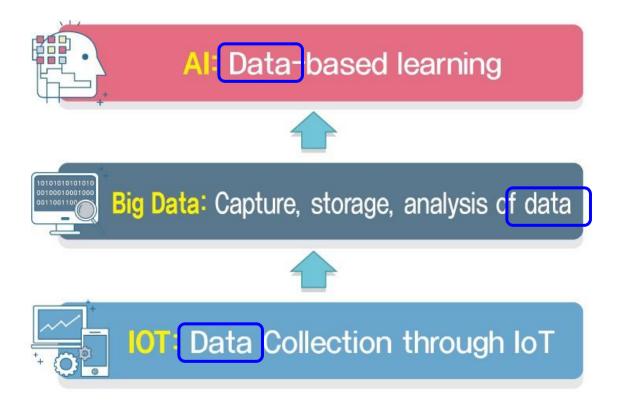
Memory Wall





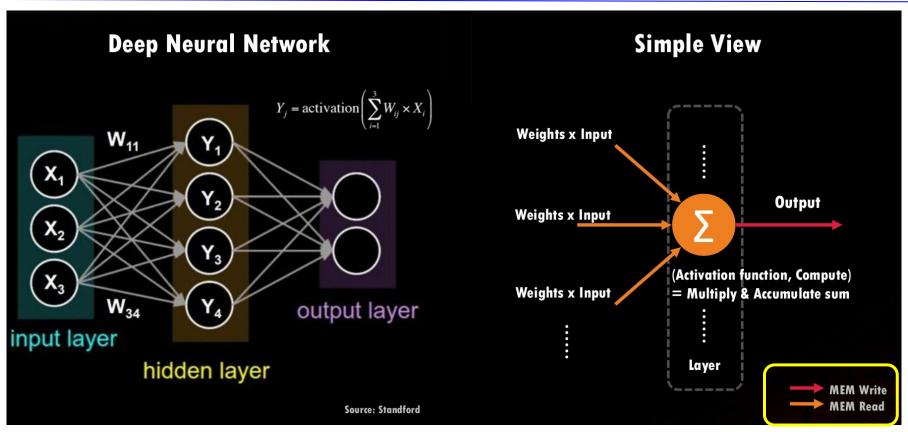
Why this is Important?





Deep Neural Network

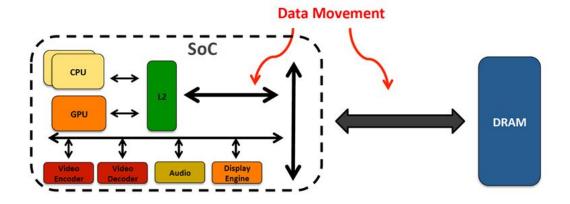




Data Movement vs. Computation Energy



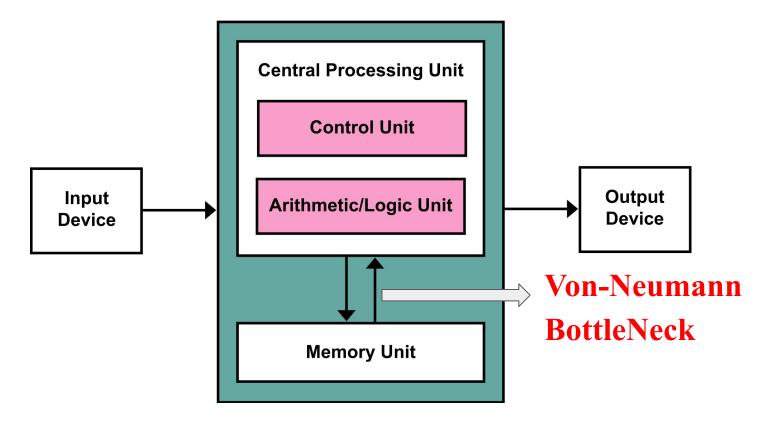
- Data movement is a major system energy bottleneck
 - Comprises 41% of mobile system energy during web browsing [2]
 - Costs ~115 times as much energy as an ADD operation [1, 2]



- [1]: Reducing data Movement Energy via Online Data Clustering and Encoding (MICRO'16)
- [2]: Quantifying the energy cost of data movement for emerging smart phone workloads on mobile platforms (IISWC'14)

Problem - Von Neumann Bottleneck

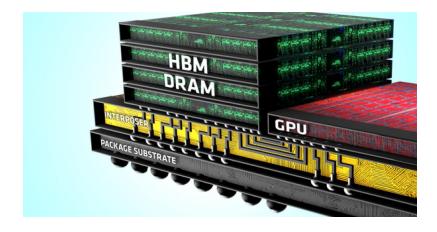




Solutions

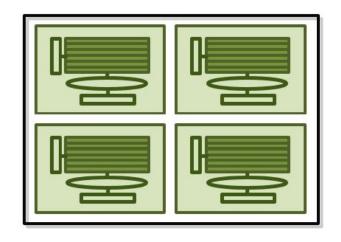


Increase Memory Bandwidth



High Bandwidth Memory

Reduce Data Movement



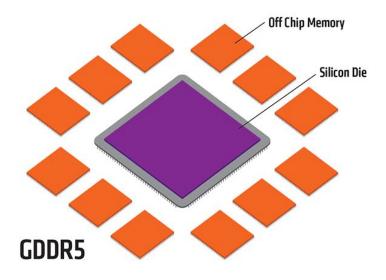
In Memory Computing

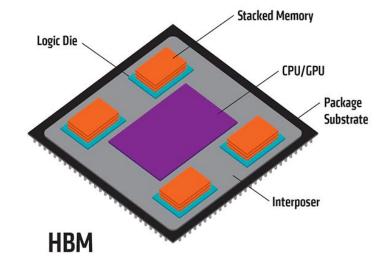


High Bandwidth Memory

High Bandwidth Memory



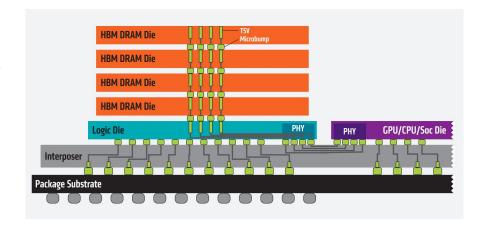




Device and Working

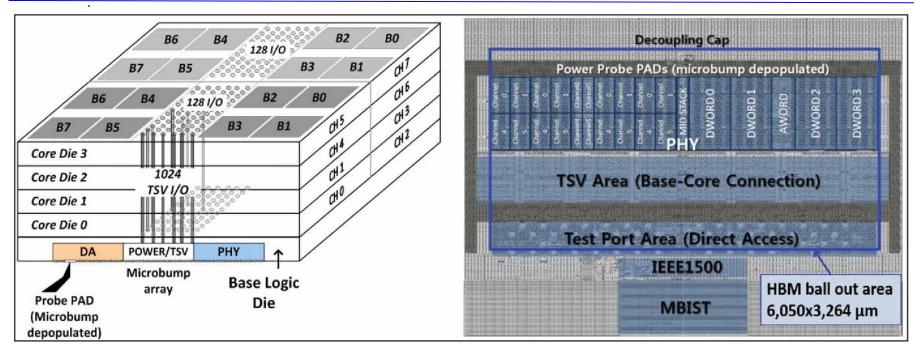


- HBM is a new type of memory chip
 - Low power consumption
 - Ultra-wide communication lanes.
- Multiple DRAM dies stacked in a single package connected by TSV and Microbumps
- Connected to the processor unit directly via Interposer Layer
- Developed by AMD and SK Hynix
- **JEDEC** industry standard in October 2013



HBM Architecture





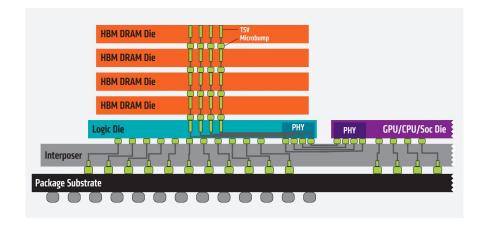
Example consisting of four DRAM core dies and one base logic die

A photo of the base die

Benefits over State of Art Memories

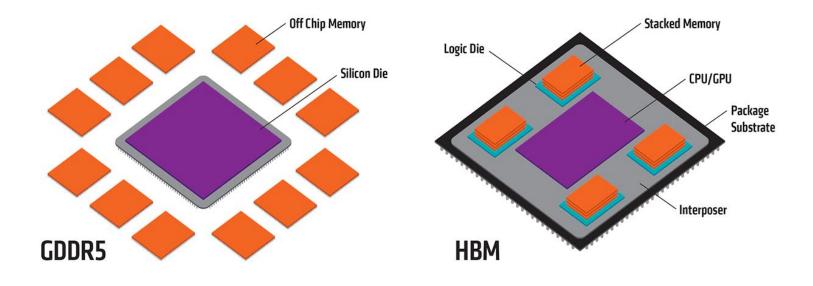


- Very **High Bandwidth**
- Lower Effective Clock Speed
- Smaller Package
- **Shorter Interconnect** Wires
- **Lower Power** Consumption



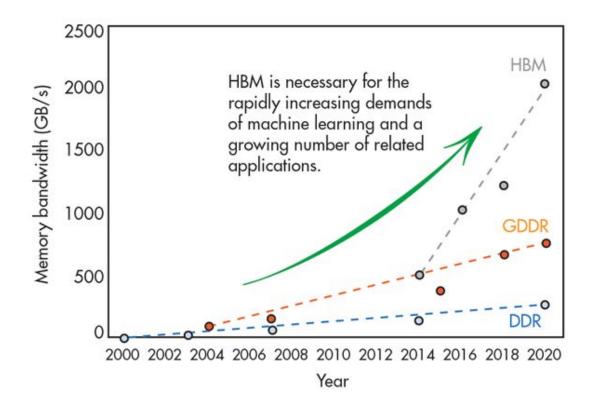
Area Savings





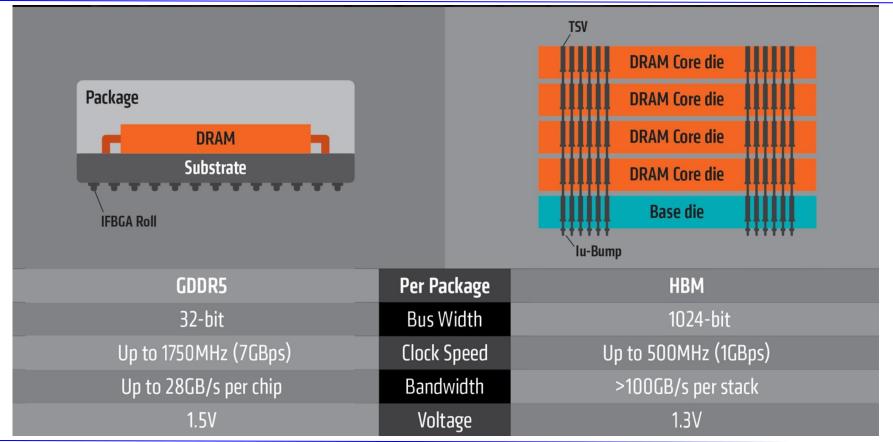
Bandwidth Improvement in HBM





Comparison - GDDR5 Vs HBM





Comparison - GDDR5 Vs HBM

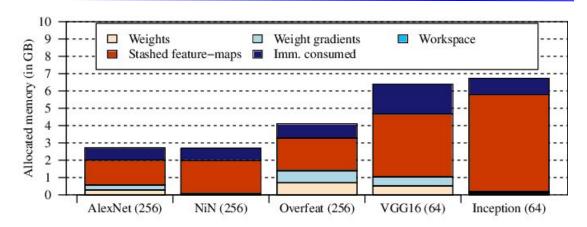


Memory	GDDR5	GDDR5X	нвм	HBM2
Manufacturer	Samsung, Hynix, Elpida	Micron	Hynix, Samsung	Samsung, Hynix
Appearance	Square / Rectangular Chip	Square / Rectangular Chip	Cube / Cuboid	Cube / Cuboid
Maximum Capacity	8GB per Die	16GB per Die	1GB per Stack	4GB / 8GB per Stack
Maximum Speed	8 Gbps	10 to 14 Gbps (16 Gbps	1 Gbps	2.4 Gbps
Bus Width	32-bit per chip	64-bit per chip	1024-bit per stack	1024-bit per stack or more
Power Consumption	Low	Same / Lower than GDDR5	and GDDR5X	Lower than HBM
Graphics Cards Used	Many Graphics Cards	GeForce GTX 1080,	Radeon R9 Fury X,	Nvidia Tesla P100, Nvidia
in	from budget, mid-range to high-end e.g. GT 740, GTX 1070, RX 480 etc.	GTX 1080 Ti, GTX 1060, Nvidia Titan X (Pascal)	Radeon Pro Duo	Quadro GP100, Radeon RX Vega 56, Radeon RX Vega 64, Nvidia Titan V, AMD Radeon VII

HBM's for AI



- High Bandwidth
- High Capacity
- Large Data Transfer Rate

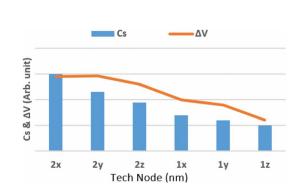


Source:A. Jain, A. Phanishayee, J. Mars, L. Tang and G. Pekhimenko, "Gist: Efficient Data Encoding for Deep Neural Network Training," 2018 ACM/IEEE 45th Annual International Symposium on Computer Architecture (ISCA), Los Angeles, CA, 2018, pp. 776-789.

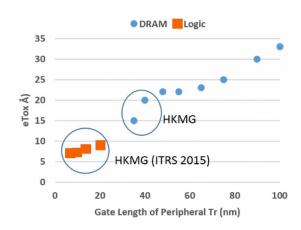
Challenges



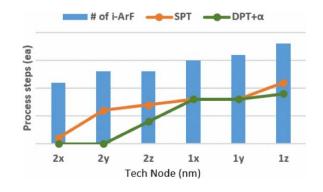
Retention Time and Sense Margin



Peripheral Transistor Performance



Chip Cost Issue and Evolutionary Approaches



Limited Capacity

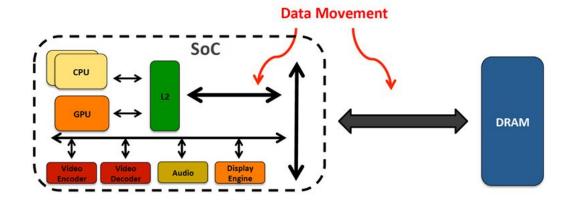


In Memory Computing

Data Movement vs. Computation Energy



- Data movement is a major system energy bottleneck
 - Comprises 41% of mobile system energy during web browsing [2]
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- [1]: Reducing data Movement Energy via Online Data Clustering and Encoding (MICRO'16)
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We Need A Paradigm Shift To ...



- Enable computation with minimal data movement
- Compute where it makes sense (where data resides)
- Make computing architectures more data-centric

Two Examples



Data Copy

Bitwise Computation

RowClone: Fast and Energy-Efficient In-DRAM Bulk Data Copy and Initialization

Vivek Seshadri vseshadr@cs.cmu.edu voongukim@cmu.edu cfallin@c1f.net donghyuk1@cmu.edu

Yoongu Kim

Chris Fallin*

Donghyuk Lee

Rachata Ausavarungnirun Gennady Pekhimenko gpekhime@cs.cmu.edu yixinluo@andrew.cmu.edu rachata@cmu.edu

Yixin Luo

Onur Mutlu

Phillip B. Gibbons[†]

Michael A. Kozuch† onur@cmu.edu phillip.b.gibbons@intel.com michael.a.kozuch@intel.com tcm@cs.cmu.edu

Todd C. Mowry

Carnegie Mellon University †Intel Pittsburgh

Ambit: In-Memory Accelerator for Bulk Bitwise Operations Using Commodity DRAM Technology

Vivek Seshadri^{1,5} Donghyuk Lee^{2,5} Thomas Mullins^{3,5} Hasan Hassan⁴ Amirali Boroumand⁵ Jeremie Kim^{4,5} Michael A. Kozuch³ Onur Mutlu^{4,5} Phillip B. Gibbons⁵ Todd C. Mowry⁵

¹Microsoft Research India ²NVIDIA Research ³Intel ⁴ETH Zürich ⁵Carnegie Mellon University

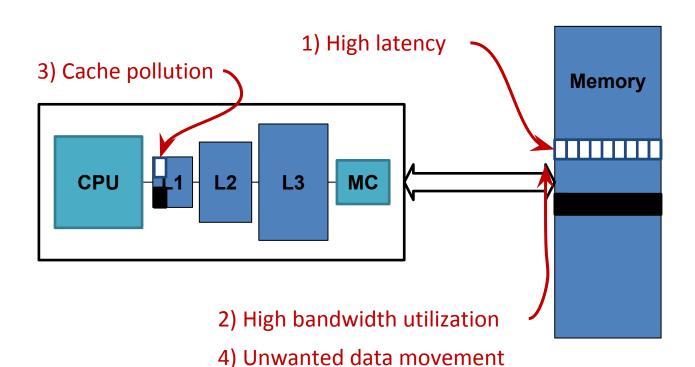


RowClone: Fast and energy-efficient in-DRAM bulk data copy and initialization

Seshadri et al., "RowClone: Fast and Efficient In-DRAM Copy and Initialization of Bulk Data," MICRO 2013.

Today's Systems: Bulk Data Copy



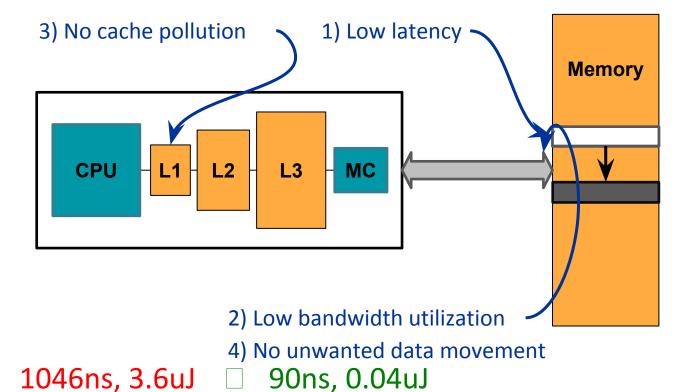


1046ns, 3.6uJ (for 4KB page copy via DMA)

Seshadri et al., "RowClone: Fast and Efficient In-DRAM Copy and Initialization of Bulk Data," MICRO 2013.

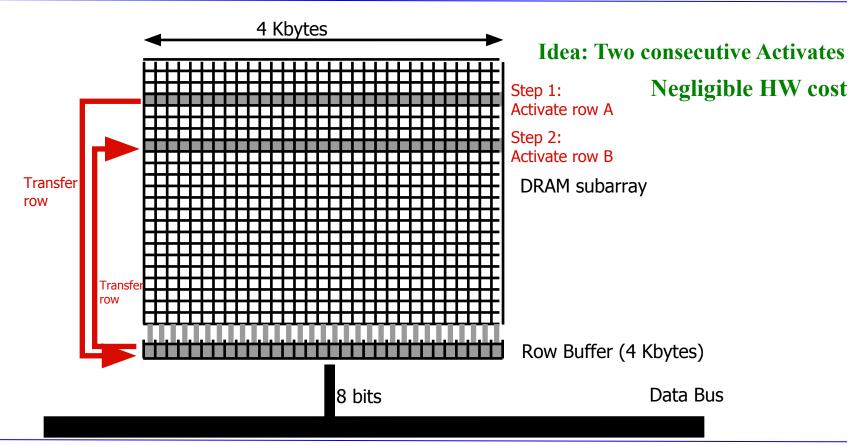
Future Systems: In-Memory Copy





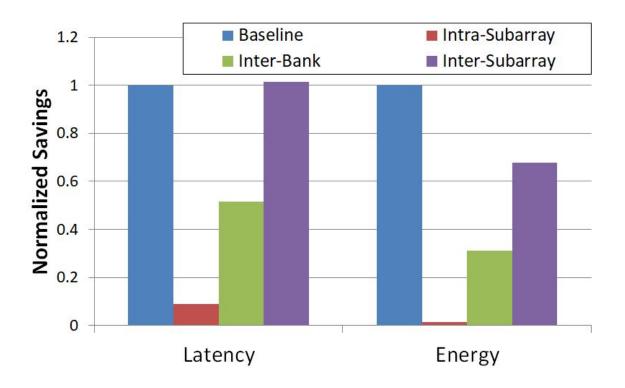
RowClone: In-DRAM Row Copy





RowClone: Latency and Energy Savings





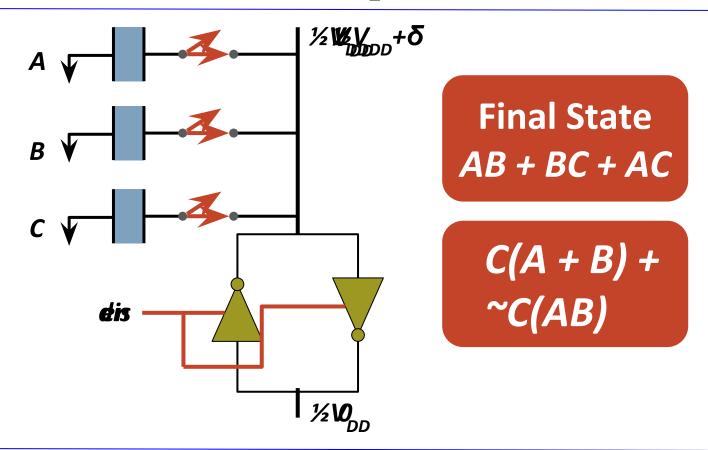


Ambit: In-Memory Accelerator for Bulk Bitwise Operations using Commodity DRAM Technology

Seshadri+, "Ambit: In-Memory Accelerator for Bulk Bitwise Operations using Commodity DRAM Technology," MICRO 2017.

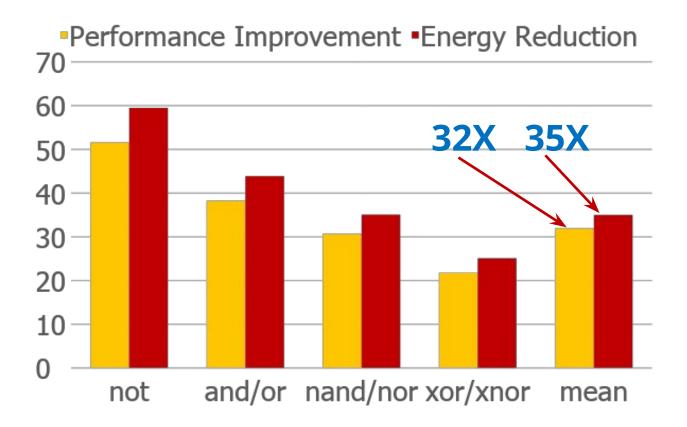
In-DRAM AND/OR: Triple Row Activation

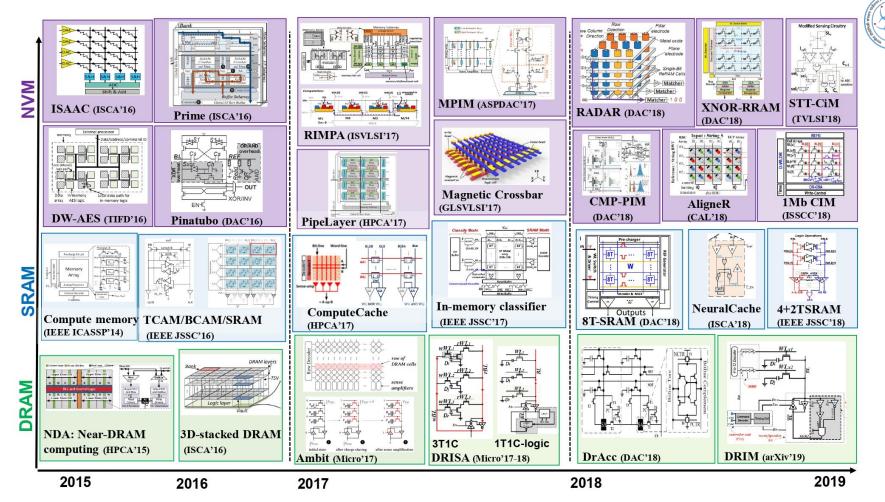




Ambit vs. DDR3: Performance and Energy

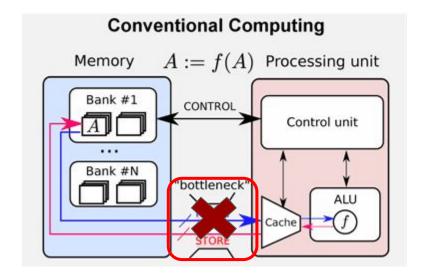


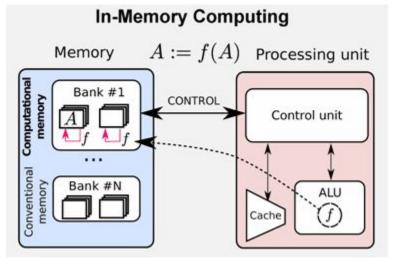




In Memory Computing for AI

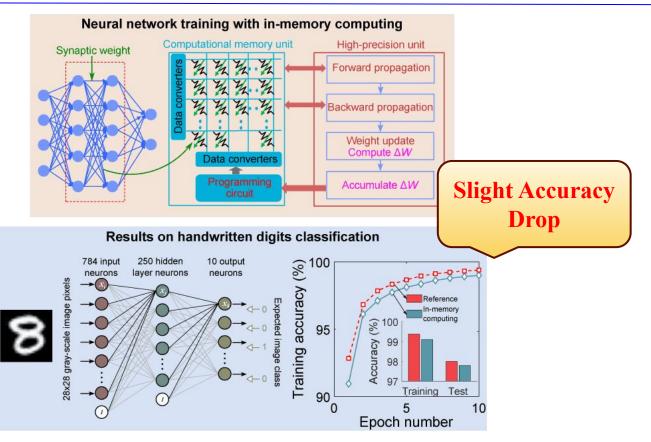






In Memory Computing for AI





Challenges - Software and Architecture



- Functionality of and applications & software for In Memory Computing
- **Ease of programming** (interfaces and compiler/HW support)
- System support: coherence & virtual memory
- Runtime and compilation systems for adaptive scheduling,
- Data mapping, access/sharing control
- **Infrastructures** to assess benefits and feasibility

Challenges - Circuits and Devices



Process Variations

- Not all Memory cells are created equal
- Some cells have **higher /lower capacitance**
 - affects the reliability of operation

• Processing Using Memory

- Exploits **analog operation** of underlying technology
- Process variation can introduce failures

Challenges

- How to design architecture to reduce impact of variations
- How to test for failures

• Intelligent Memory Controllers

ECC Circuits



HBM or In Memory Computing?

nanoDC Lab



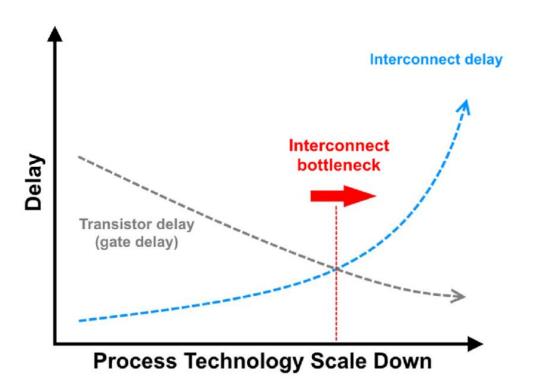
Both.

Better Way: In Memory Compute in HBM

nanoDC Lab

Why?

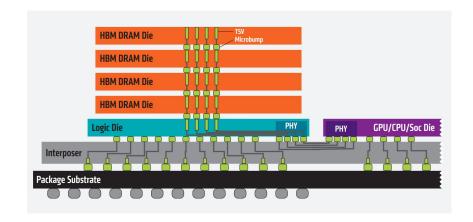




Why?



- Interconnects
 - Large Power consumption
 - Capacitance
 - Metal lines
- Large Interconnect Delay compared to Gate delay
- Logic Layer beneath DRAM dies
 - Support In Memory Computing



Conclusion



In Memory Compute in HBM.

Some Recent works on IMC in HBM



A 3D-Stacked Logic-in-Memory Accelerator for Application-Specific Data Intensive Computing

Qiuling Zhu, Berkin Akin, H. Ekin Sumbul, Fazle Sadi, James C. Hoe, Larry Pileggi, Franz Franchetti Dept. of Electrical and Comp. Eng., Carnegie Mellon University, Pittsburgh, PA, USA Email: {qiulingz,bakin,hsumbul,fsadi,jhoe,pileggi,franzf}@ece.cmu.edu

Session 10: Memory Architectures

GLSVLSI'18, May 23-25, 2018, Chicago, IL, USA

A Compiler for Automatic Selection of Suitable Processing-in-Memory Instructions

Hameeza Ahmed, Paulo C. Santos[†], João P. C. Lima[†], Rafael F. Moura[†], Marco A. Z. Alves[‡], Antônio C. S. Beck[†], Luigi Carro[†] Dep. of Computer and Information Systems Eng. - NED University - Karachi, Pakistan [†]Informatics Institute - Federal University of Rio Grande do Sul - Porto Alegre, Brazil [‡]Department of Informatics - Federal University of Paraná - Curitiba, Brazil Email: hameeza@neduet.edu.pk †{pcssjunior, jplima, rfmoura, caco, carro}@inf.ufrgs.br ‡{mazalves}@inf.ufpr.br

Towards Near-Data Processing of Compare Operations in **3D-Stacked Memory**

Palash Das and Hemangee K. Kapoor Department of CSE, IIT Guwahati, Guwahati, Assam 781039, India {palash.das, hemangee}@iitg.ernet.in

IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS, VOL. 30, NO. 3, MARCH 2019

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Exploiting Parallelism for CNN Applications on 3D Stacked Processing-In-Memory Architecture

Yi Wang[®], Member, IEEE, Weixuan Chen[®], Jing Yang, and Tao Li, Fellow, IEEE

Design space exploration for PIM architectures in 3D-stacked memories

João Paulo C. de Lima Fed. University of Rio Grande do Sul Porto Alegre, RS, Brazil

Paulo Cesar Santos Fed. University of Rio Grande do Sul Porto Alegre, RS, Brazil

Marco A. Z. Alves Fed. University of Paraná Curitiba, PR, Brazil

Antonio C. S. Beck Porto Alegre, RS, Brazil

Luigi Carro Fed. University of Rio Grande do Sul Fed. University of Rio Grande do Sul Porto Alegre, RS, Brazil

Conclusion



- Von-Neumann Bottleneck
- Solutions
 - High Bandwidth Memory
 - In Memory Computing
- In Memory Computing in HBM's
 - o Increase Bandwidth
 - Reduce Data Movement

References



- 1. Moore, Gordon E. "Cramming more components onto integrated circuits." (1965): 114-117.
- 2. Chu, Yaohan, ed. High-level language computer architecture. Academic Press, 2014.
- 3. Seshadri, Vivek, et al. "Ambit: In-memory accelerator for bulk bitwise operations using commodity DRAM technology." Proceedings of the 50th Annual IEEE/ACM International Symposium on Microarchitecture. ACM, 2017.
- 4. Seshadri, Vivek, et al. "RowClone: fast and energy-efficient in-DRAM bulk data copy and initialization." Proceedings of the 46th Annual IEEE/ACM International Symposium on Microarchitecture. ACM, 2013.
- 5. Seshadri, Vivek, et al. "Fast bulk bitwise AND and OR in DRAM." IEEE Computer Architecture Letters 14.2 (2015): 127-131.
- 6. Wang, Shibo, and Engin Ipek. "Reducing data movement energy via online data clustering and encoding." The 49th Annual IEEE/ACM International Symposium on Microarchitecture. IEEE Press, 2016.
- 7. H. Jun et al., "HBM (High Bandwidth Memory) DRAM Technology and Architecture," 2017 IEEE International Memory Workshop (IMW), Monterey, CA, 2017, pp. 1-4.
- 8. Mohsen Imani, Saransh Gupta, Yeseong Kim, and Tajana Rosing. 2019. FloatPIM: in-memory acceleration of deep neural network training with high precision. In Proceedings of the 46th International Symposium on Computer Architecture (ISCA '19). ACM, New York, NY, USA, 802-815.
- 9. S. Lee, "Technology scaling challenges and opportunities of memory devices," 2016 IEEE International Electron Devices Meeting (IEDM), San Francisco, CA, 2016, pp. 1.1.1-1.1.8.



Thank You