Future of Computing: Moore's Law, The End of Frequency Scaling, Domain-specific accelerators

15-213: Introduction to Computer Systems 27th Lecture, Apr. 28, 2022

Instructor:

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Moore's Law Origins



April 19, 1965



Cramming more components onto integrated circuits

With unit cost falling as the number of components per circuit rises, by 1975 economics may dictate squeezing as many as 65,000 components on a single silicon chip

By Gordon E. Moore

Director, Research and Development Laboratories, Fairchild Semiconductor division of Fairchild Camera and Instrument Corp.

Moore's Law Origins



Moore's Thesis

- Minimize price per device
- Optimum number of devices / chip increasing 2x / year

Later

- **2x / 2 years**
- "Moore's Prediction"

Moore's Law: 50 Years

Transistor Count by Year



What Moore's Law Has Meant



1976 Cray 1

- 250 M Ops/second
- ~170,000 chips
- 0.5B transistors
- **5,000 kg, 115 KW**
- \$9M
- 80 manufactured

2014 iPhone 6

- > 4 B Ops/second
- ~10 chips
- > 3B transistors
- 120 g, < 5 W
- \$649
- 10 million sold in first 3 days

What Moore's Law Has Meant

1965 Consumer Product



2015 Consumer Product





Apple A8 Processor 2 B transistors

Visualizing Moore's Law to Date

If transistors were the size of a grain of sand

Intel 4004 1970 2,300 transistors





0.1 g

Apple A8 2014 2 B transistors





88 kg

Moore's "Law" drove itself



What Moore's Law Could Mean

2015 Consumer Product



2065 Consumer Product



- Portable
- Low power
- Will drive markets & innovation

Requirements for Future Technology

Must be suitable for portable, low-power operation

- Consumer products
- Internet of Things components
- Not cryogenic, not quantum

Must be inexpensive to manufacture

- Comparable to current semiconductor technology
 - O(1) cost to make chip with O(N) devices

Need not be based on transistors

- Memristors, carbon nanotubes, DNA transcription, ...
- Possibly new models of computation
- But, still want lots of devices in an integrated system

Increasing Transistor Counts

1. Chips have gotten bigger

1 area doubling / 10 years

2. Transistors have gotten smaller

4 density doublings / 10 years

Will these trends continue?

Chips Have Gotten Bigger

Intel 4004 1970 2,300 transistors 12 mm²



Apple A8 2014 2 B transistors 89 mm²



IBM z13 205 4 B transistors 678 mm²





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Chip Size Trend

Area by Year



Chip Size Extrapolation

Area by Year



Extrapolation: The iPhone 31s

Apple A59 2065 10¹⁷ transistors





Transistors Have Gotten Smaller

- Area A
- *N* devices $L = \sqrt{A/N}$
- Linear Scale L



Linear Scaling Trend

Linear Scale by Year



Decreasing Feature Sizes

Intel 4004 1970 2,300 transistors *L* = 72,000 nm

Apple A8 2014 2 B transistors L = 211 nm



Linear Scaling Trend



Submillimeter Dimensions



Submicrometer Dimensions



Linear Scaling Extrapolation

Linear Scale by Year



Subnanometer Dimensions



Reaching 2065 Goal

Target

- 10¹⁷ devices
- 400 mm²
- *L* = 63 pm





Is this possible?



Not with 2-d fabrication

Moore's Law: The number of transistors on microchips has doubled every two years Our World

Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important for other aspects of technological progress in computing – such as processing speed or the price of computers.



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in Data

Our World in Data

Historical cost of computer memory and storage

Measured in US dollars per megabyte.



Source: John C. McCallum (2022)

Note: For each year the time series shows the cheapest historical price recorded until that year.

Fabrication Economics

Currently

- Fixed number of lithography steps
- Manufacturing cost \$10-\$20 / chip
 - Including amortization of facility

Fabricating 1,000,000 physical layers

Cannot do lithography on every step

Options

- Chemical self assembly
 - Devices generate themselves via chemical processes
- Pattern multiple layers at once



Challenges to Moore's Law: Economic

Altis

Grace

SMIC

Bryant and O'Hall

Semiconductor

Dongbu HiTek

Semiconductor

Dongbu HiTek

Semiconductor

Grace

SMIC

	Growing	Capital	Costs
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- State of art fab line ~\$20B
- Must have very high volumes to amortize investment
- ns

130nm	90nm	65nm	45/40nm	32/28nm	22/20nm	
Samsung	Samsung	Samsung	Samsung	Samsung	Samsung	
Intel	Intel	Intel	Intel	Intel	Intel	
STMicroelectronics	STMicroelectronics	STMicroelectronics	STMicroelectronics	STMicroelectronics	Globalfoundries	
Toshiba	Toshiba	Toshiba	Toshiba	Globalfoundries	TSMC	
Fujitsu	Fujitsu	Fujitsu	Fujitsu	TSMC		
IBM	IBM	IBM	IBM	UMC		
Renesas (NEC)	Renesas	Renesas	Renesas		i i i i i i i i i i i i i i i i i i i	
l exas Instruments	Instruments	Instruments	Globalfoundries			
Sony	Sony	Sony	TSMC			
Infineon	Infineon	Infineon	UMC			
Freescale	Freescale	Globalfoundries	SMIC			
Seiko Epson	Seiko Epson	TSMC	a designed and the second s			
Globalfoundries	Globalfoundries	UMC				
TSMC	TSMC	SMIC	Has led to major consolidation			
UMC	UMC					

Meeting Power Constraints



- 2 B transistors
- 2 GHz operation
- 1—5 W

Can we increase number of devices by 500,000x without increasing power requirement?



- 64 B neurons
- 100 Hz operation
- 15—25 W
 - Liquid cooling
 - Up to 25% body's total energy consumption

End of Dennard Scaling



What Happened?

- Old: Reduce voltage as we reduced transistor size
- New: Can't drop voltage below ~1V
- Reached limit of power / chip in 2004
- More logic on chip (Moore's Law), but can't make them run faster
 - Response has been to increase cores / chip

End of Easy Gains – Fun Times Ahead

- We can't just crank up the clock
- We won't be able to infinitely add cores
- We want to keep improving perf/\$, perf/W, etc.
- But we're going to have to be even more clever at all layers of the computation stack...

Samsung V-Nand Flash Example





- Build up layers of unpatterned material
- Then use lithography to slice, drill, etch, and deposit material across all layers
- ~30 total masking steps
- Up to 48 layers of memory cells
- Exploits particular structure of flash memory circuits

Putting Parallelism on the Programmer





A lot of parallelism...



At 350W, a lot of power, too

Google Data Centers





Dalles, Oregon

- Hydroelectric power @ 2¢ / KW Hr
- 50 Megawatts
- Enough to power 60,000 homes

- Engineered for low cost, modularity & power efficiency
- Container: 1160 server nodes, 250KW

Cluster Programming Model

- Application programs written in terms of high-level operations on data
- Runtime system controls scheduling, load balancing, ...

Scaling Challenges

- Centralized scheduler forms bottleneck
- Copying to/from disk very costly
- Hard to limit data movement
 - Significant performance factor









DNN Application Example

Facebook DeepFace Architecture









The "More than Moore" approach

- "Functional diversification of semiconductor-based devices"
 - Integration of sensors, RF, MEMS, quantum?, storage

GlobalFoundries Stops All 7nm Development: Opts To Focus on Specialized Processes

by Anton Shilov & Ian Cutress on August 27, 2018 4:01 PM EST

Flowering of application-specific chips







ASICs in the wild at gigacorps

- Google: TPUv1, v2, v3, custom network interface card, video transcoder,
- Amazon: Al chip, custom VM controller, custom switching chip
- Apple: Its own ARM chips, M1, custom AI chip



6 core CPU, 5 core GPU, 16 core Neural Engine, ISP image processor, Hardware video codec



We will have more advances

- But they're bumpy!
- Optical interconnects give us a one time big bump
- Persistent memory might still but bumpy
- We have more lithographic advances but really hard
- We have yield improvements for EUV but slowing over time...

Adding accelerators



Implementation Complexity

Can't outrun Amdahl

Moore:

- Most CPU functions got faster simultaneously
- Memory density scaled too!
- I/O (& mem latency) was the primary bottleneck to work around

Multicore:

Parallelization bottleneck

GPUs / SIMD

Vectorization & parallelization

Post-Moore:

Specialization bottleneck

Future speedups will need it all...

- Hardware improvements
- Specialized hardware/software co-design
- Software implementation improvements
- Algorithmic improvements

4096 x 4096 Matrix Multiply

Implementation	$Running time \ (s)$	GFLOPS	$\begin{array}{c} Absolute \\ speedup \end{array}$
Python	$25,\!552.48$	0.005	1
Java	$2,\!372.68$	0.058	11
\mathbf{C}	542.67	0.253	47
Parallel loops	69.80	1.969	366
Parallel divide-and-conquer	3.80	36.180	6,727
+ vectorization	1.10	124.914	$23,\!224$
+ AVX intrinsics	0.41	337.812	62,806

(Leiserson et al., "There's Plenty of Room At The Top")

MaxFlow over time (Leiserson et al)



2018--?: Putting Heterogeneity on the programmer

- Trend in architecture over last decade: Increasingly shift pain to the programmer
 - Parallelization, vectorization, massive concurrency, etc.
- This will get worse. (No alternative yet)



Heterogenous, experts-only Hardware

Bryant and O'Hallaron, Computer Systems: A Programmer's Perspective, Third Edition

Narrow Waists

Waists are emerging: ML example



TPUs v1-3, EdgeTPU, Neural Compute Stick, A12 Bionic, Intel FPGA DLIA, GPUs, x86, ARM,

How do we manage?

- By making sure we combine systems knowledge + domain knowledge to craft frameworks that help programmers get things done in this increasingly complex hardware world
- Go forth and build awesome systems!