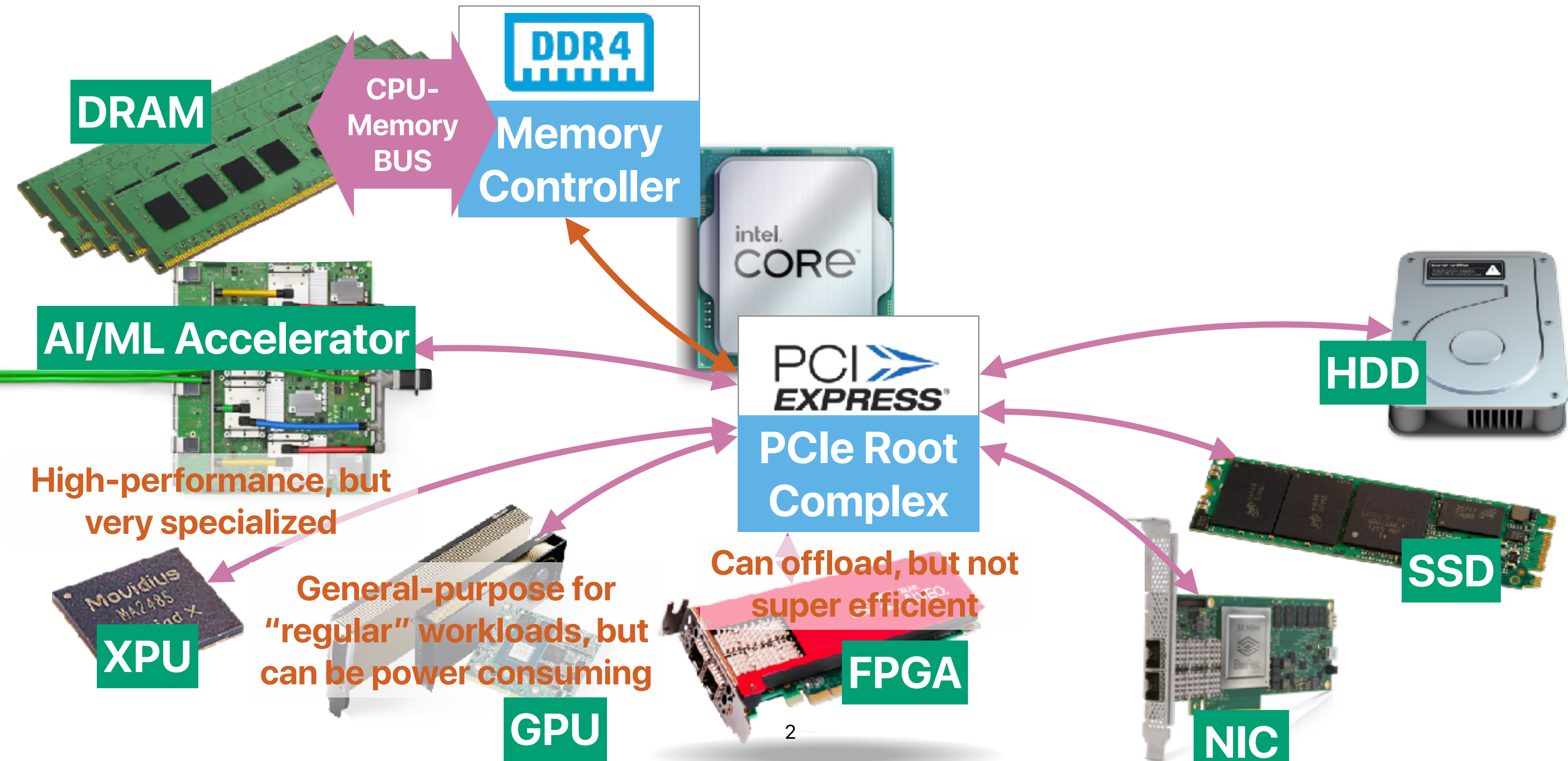


Memory subsystem

Hung-Wei Tseng

Recap: The landscape of modern computers



Recap: Approx. on NPU v.s. GPTPU

	Approx. on NPU	GPTPU
Performance	Better if the algorithm is more complex, but worse otherwise	Depending on the complexity of the algorithm
Result quality	Approximate, not accurate	Exact — if the hardware supports the desired precision
Programming efforts	Easier — the programmer does not need to take care of programming on AI/ML accelerators	Difficult — the programmer has to map the computation into operators that the hardware supports
Applicability	Any algorithm on an application tolerating inexactness	Only algorithms that map well to the hardware architecture

Recap: TCUDB

```
SELECT A.customer, B.brand, SUM(A.Quantity * B.Price) AS value FROM A INNER JOIN B WHERE ON A.ProductIDA = B.ProductID GROUP BY A.customer, B.brand;
```

Customer	ProductID	Brand	Quant.
Abe	i9-12900	Intel	1
Abe	i7-12700	Intel	1
Abe	RTX3080	NVIDIA	1
Abe	660p	Intel	2
Bob	RyZen 5800G	AMD	1
Bob	980Pro	Samsung	1
Cindy	RTX3080	NVIDIA	1
Cindy	i7-12700	Intel	2
Cindy	660p	Intel	2
Diana	RyZen 5800G	AMD	1
Diana	RX5000	AMD	1
Diana	980Pro	Samsung	1

$O(n)$

Brand	ProductID	Price
Intel	i9-12900	600
Intel	i7-12700	400
Intel	660p	100
AMD	RX5000	500
AMD	RyZen 5800G	200
NVIDIA	RTX3080	1200
Samsung	980Pro	100

Customer	Intel	AMD	NVIDIA	Samsung
Abe	1200	0	1200	0
Bob	0	400	0	100
Cindy	1000	0	1200	0
Diana	0	900	0	100

Matrix multiplications
 $O(m \times n \times k)$

Left

Customer/ ProductID	i9-12900	i7-12700	660p	RX5000	RyZen 5800G	RTX3080	980Pro
Abe	1	1	2	0	0	1	0
Bob	0	0	0	0	1	0	1
Cindy	0	2	2	0	0	1	0
Diana	0	0	0	1	1	0	1

OP! — This could be done by 1 Tensor Core

ProductID/ Brand	Intel	AMD	NVIDIA	Samsung
i9-12900	600	0	0	0
i7-12700	400	0	0	0
660p	100	0	0	0
RX5000	0	500	0	0
RyZen 5800G	0	400	0	0
RTX3080	0	0	1200	0
980Pro	0	0	0	100



Memory copy

$O(m)$

Recap: Similarities between kNN and Ray Tracing

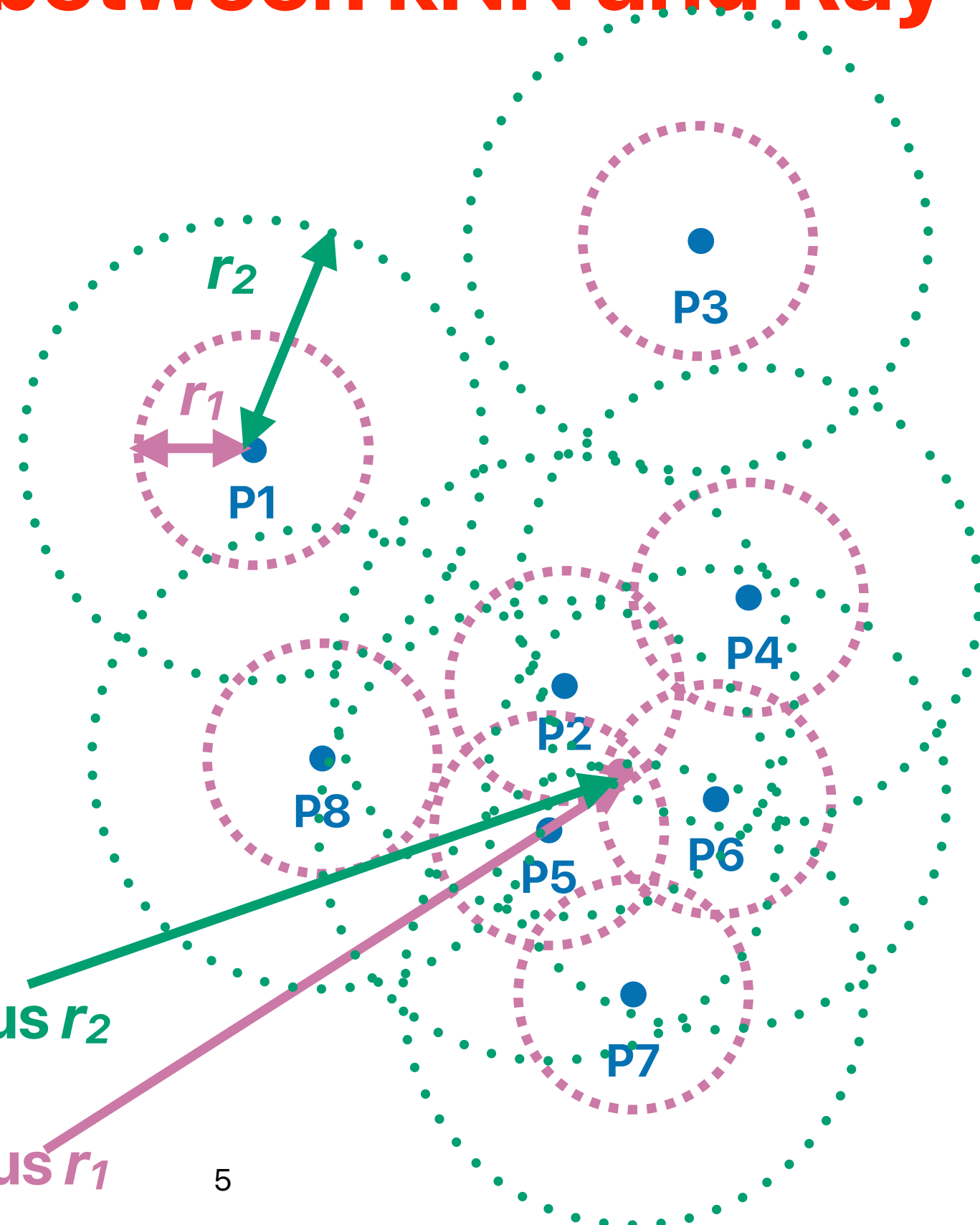
Assume we want to find "5" NN

Answer: P2, P4, P5, P6, P7

Answer: P2, P5, P6

Q_1 with radius r_2

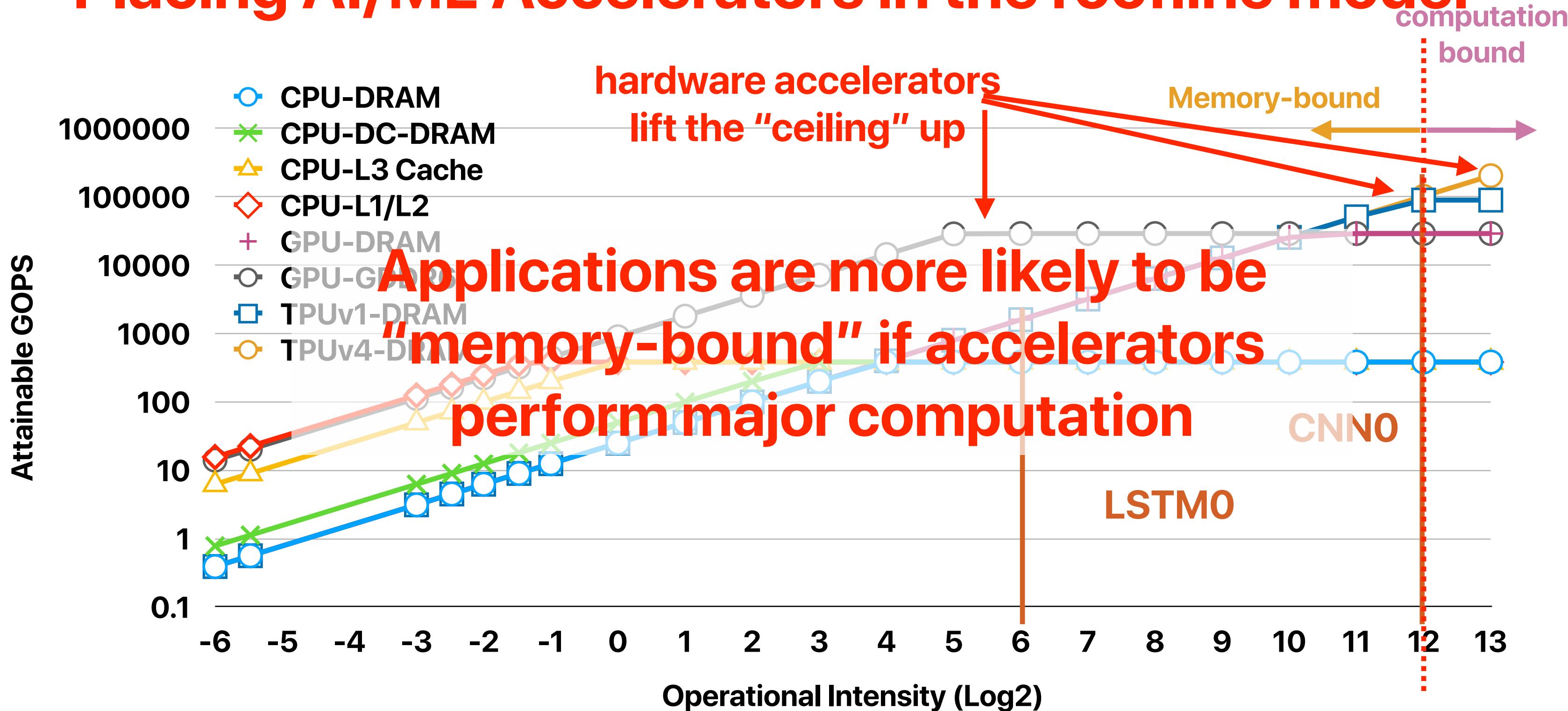
Q_1 with radius r_1



Recap: Summary of General-purpose computing on "something"

- Map your problem as a problem that the target hardware can solve
 - Machine learning models (NPU)
 - Machine learning mathematical operations (GP Edge TPU)
 - Matrix multiplications (TCUDB)
 - Ray Tracing (RTNN)
- Due to the domain specific nature of accelerators, we have to program in a more domain specific way, "currently".
- Not necessarily the most performant, but typically more energy-efficient

Placing AI/ML Accelerators in the roofline model



Outline

- Memory

What are potential approaches to lift the roofline on memory-bound applications?

Ideas of improving memory-bound programs?

Shifting the roofline

- Faster memory technologies
- Higher memory bandwidth
- Lower data volume

Memory technologies

What kinds of memory technologies are presented in modern computer systems? Strength? Weakness?

Memory technologies we have today

Volatile v.s. Non-volatile

- Volatile memory
 - The stored bits will vanish if the cell is not supplied with electricity
 - Register, SRAM, DRAM
- Non-volatile memory
 - The stored bits will not vanish “immediately” when it’s out of electricity — usually can last years
 - Flash memory, PCM, MRAM, STTRAM

Memory technologies we have today

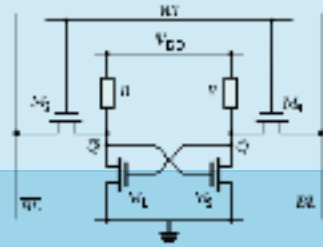
- SRAM
- DRAM
- Registers
- PCM
- 3DXPoint
- RRAM
- Flash memory

Memory technologies we have today

Volatile Memory

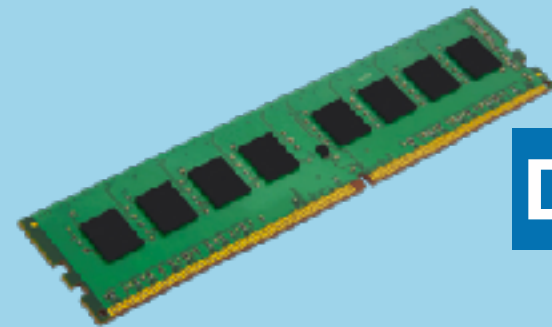
Non-Volatile Memory

100ps



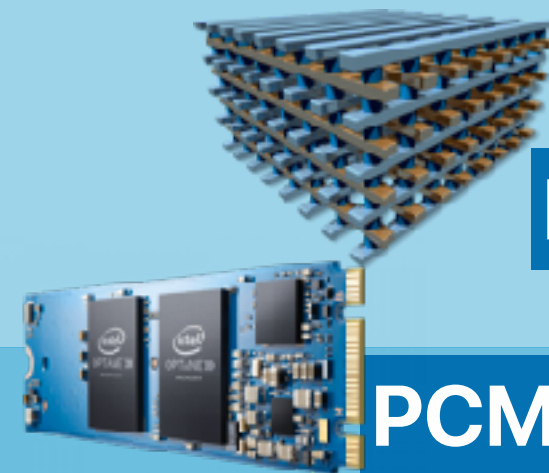
SRAM

ns



DRAM

us



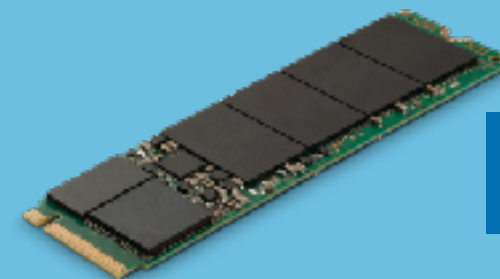
RRAM



PCM

3DXPoint

ms

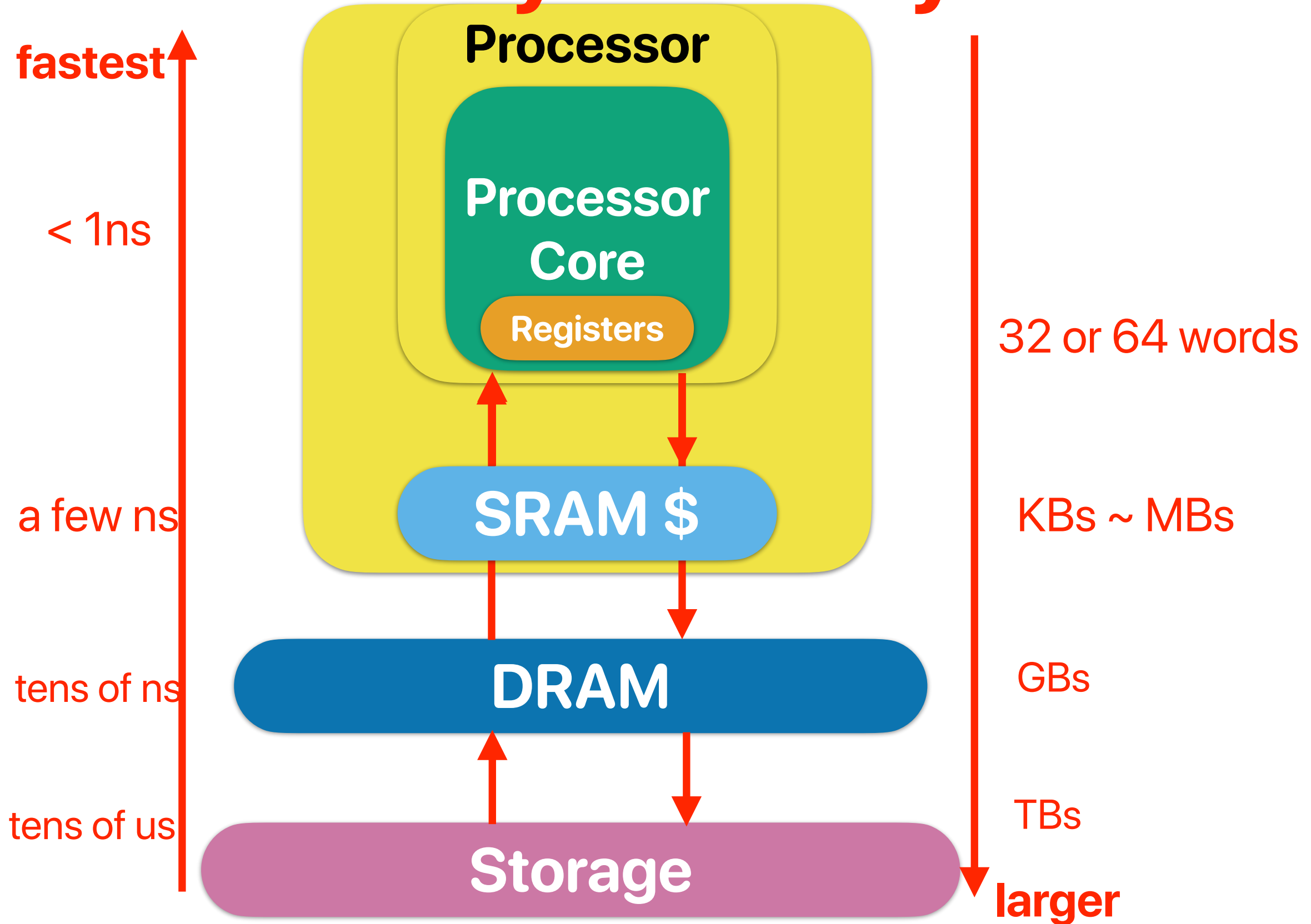


Flash memory



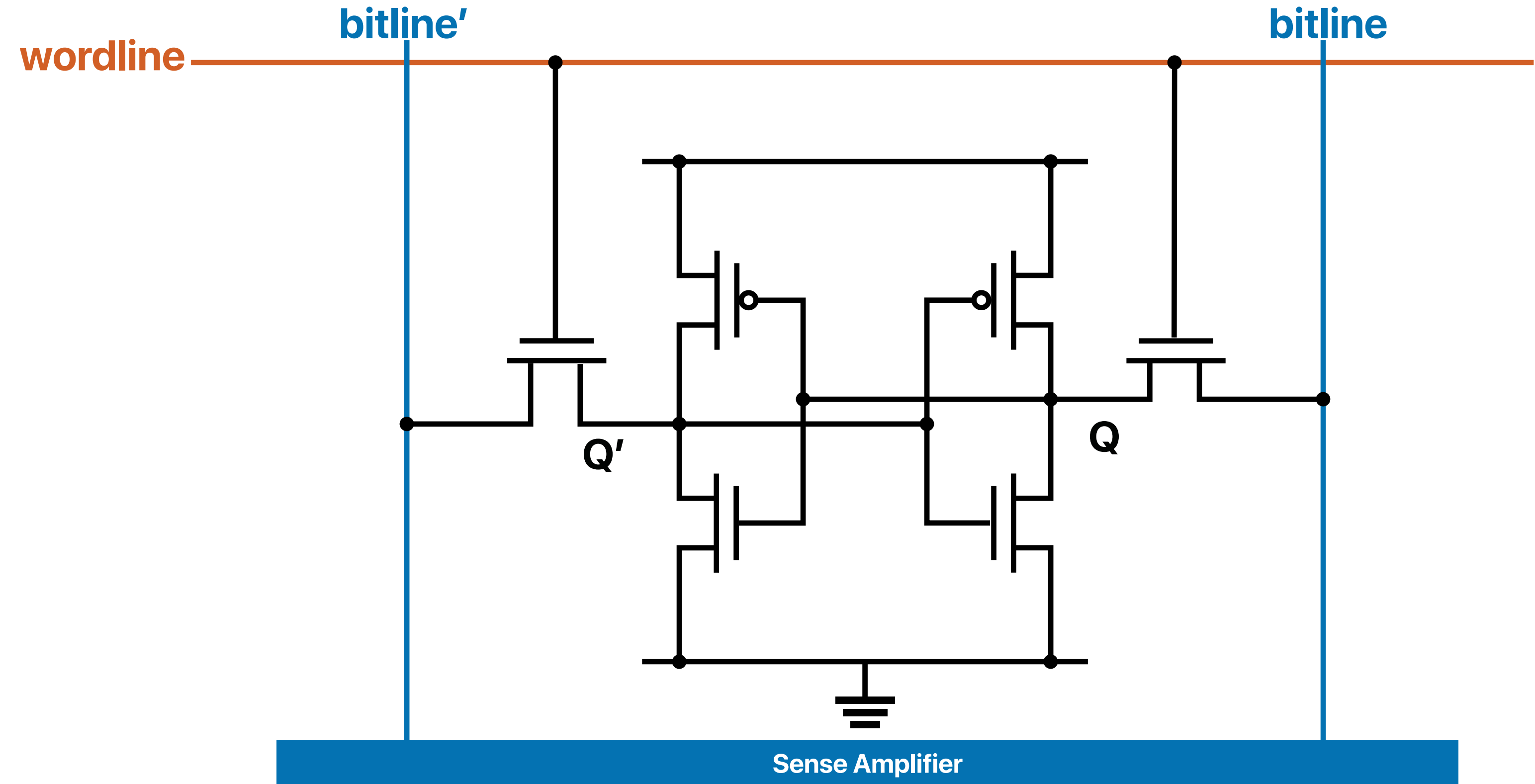
Hard Disk Drives

Memory Hierarchy

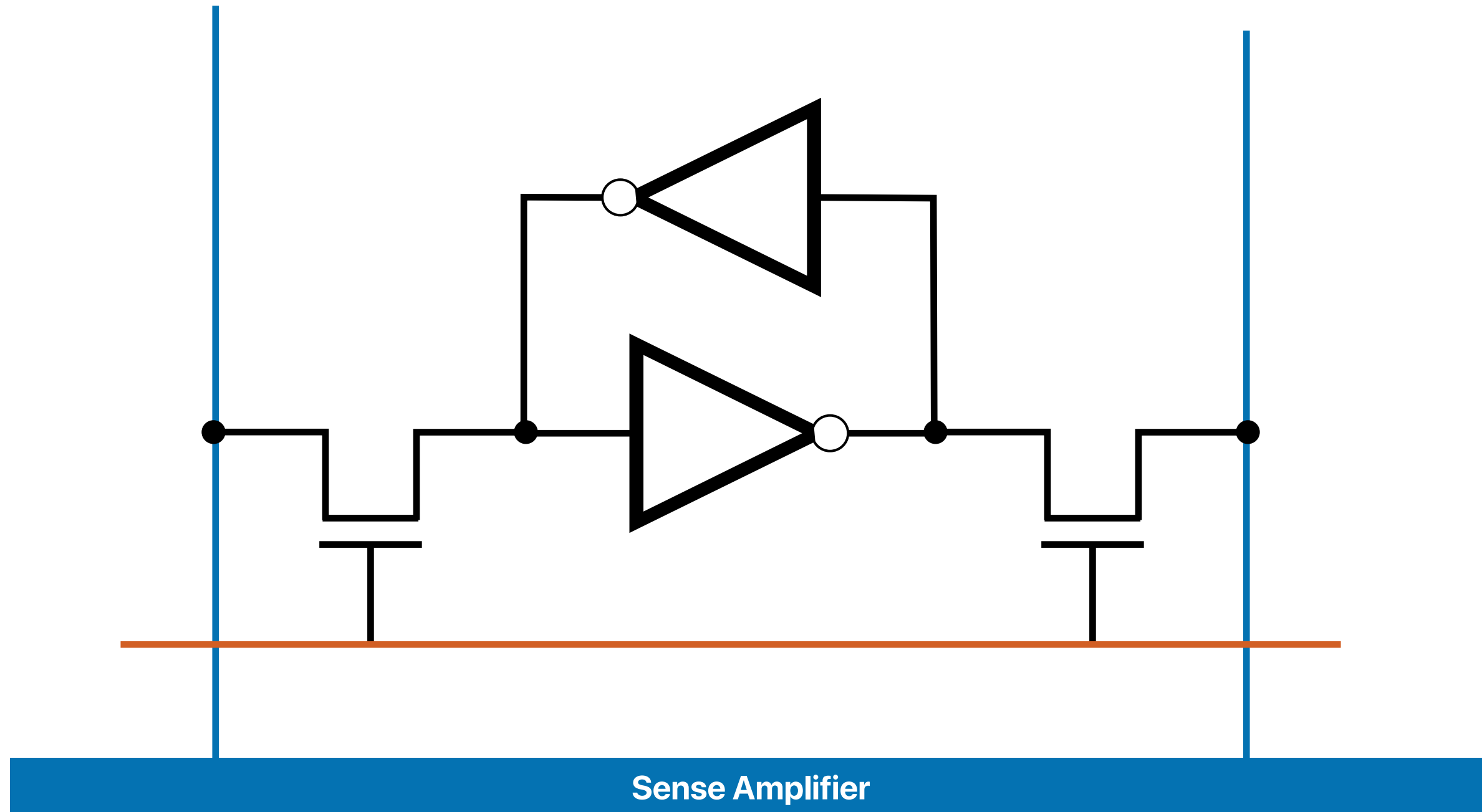


Static Random Access Memory (SRAM)

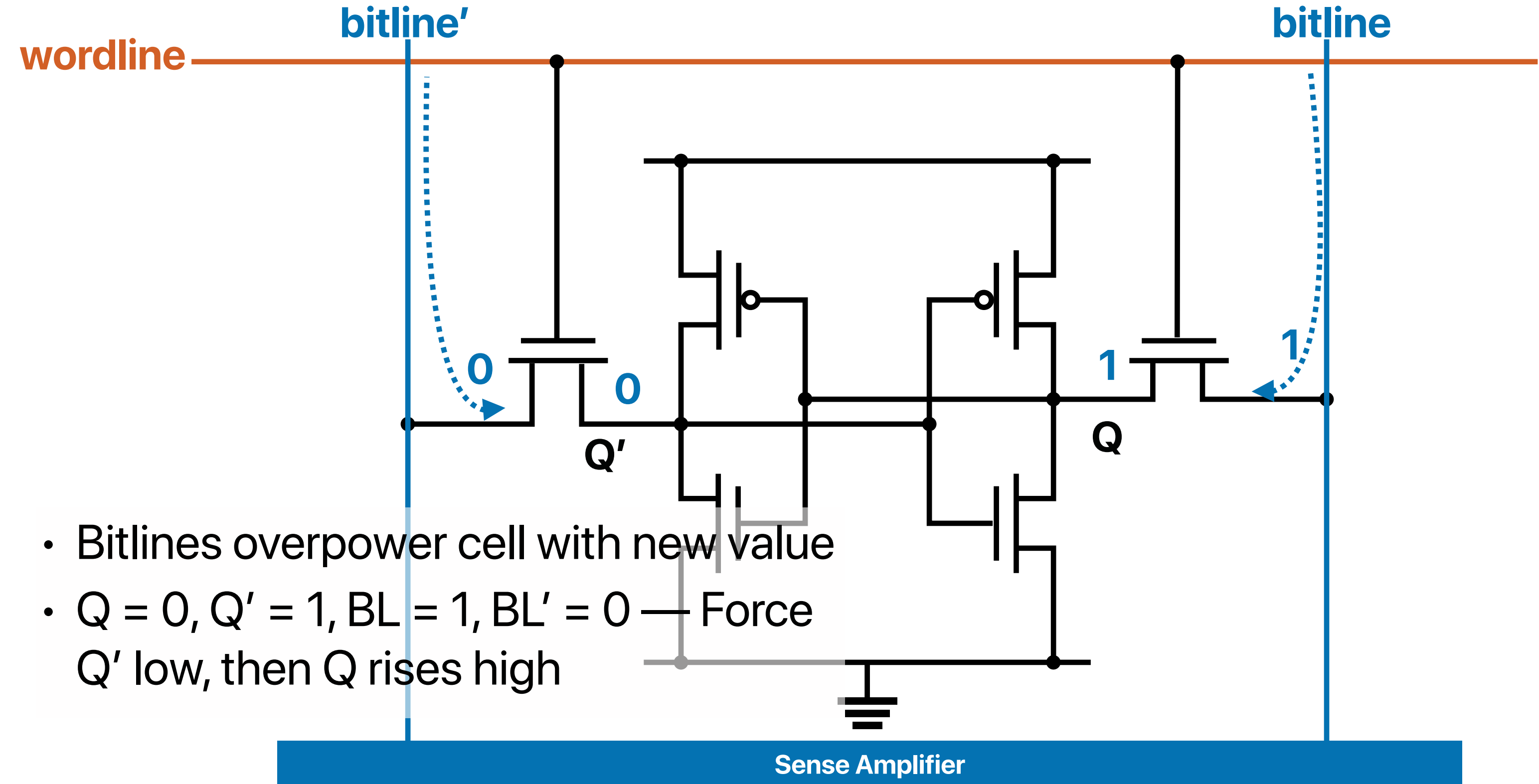
A Classical 6-T SRAM Cell



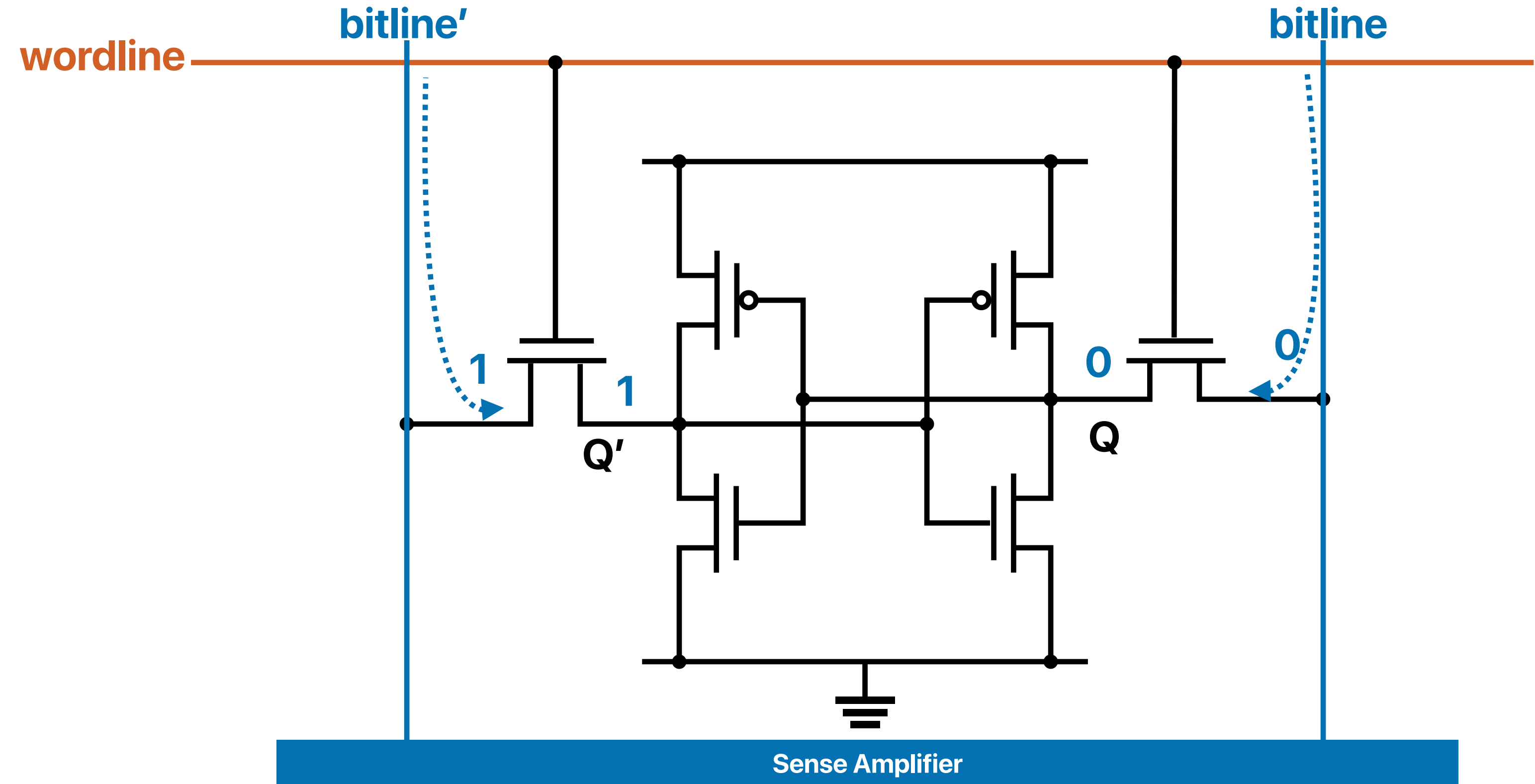
A Classical 6-T SRAM Cell



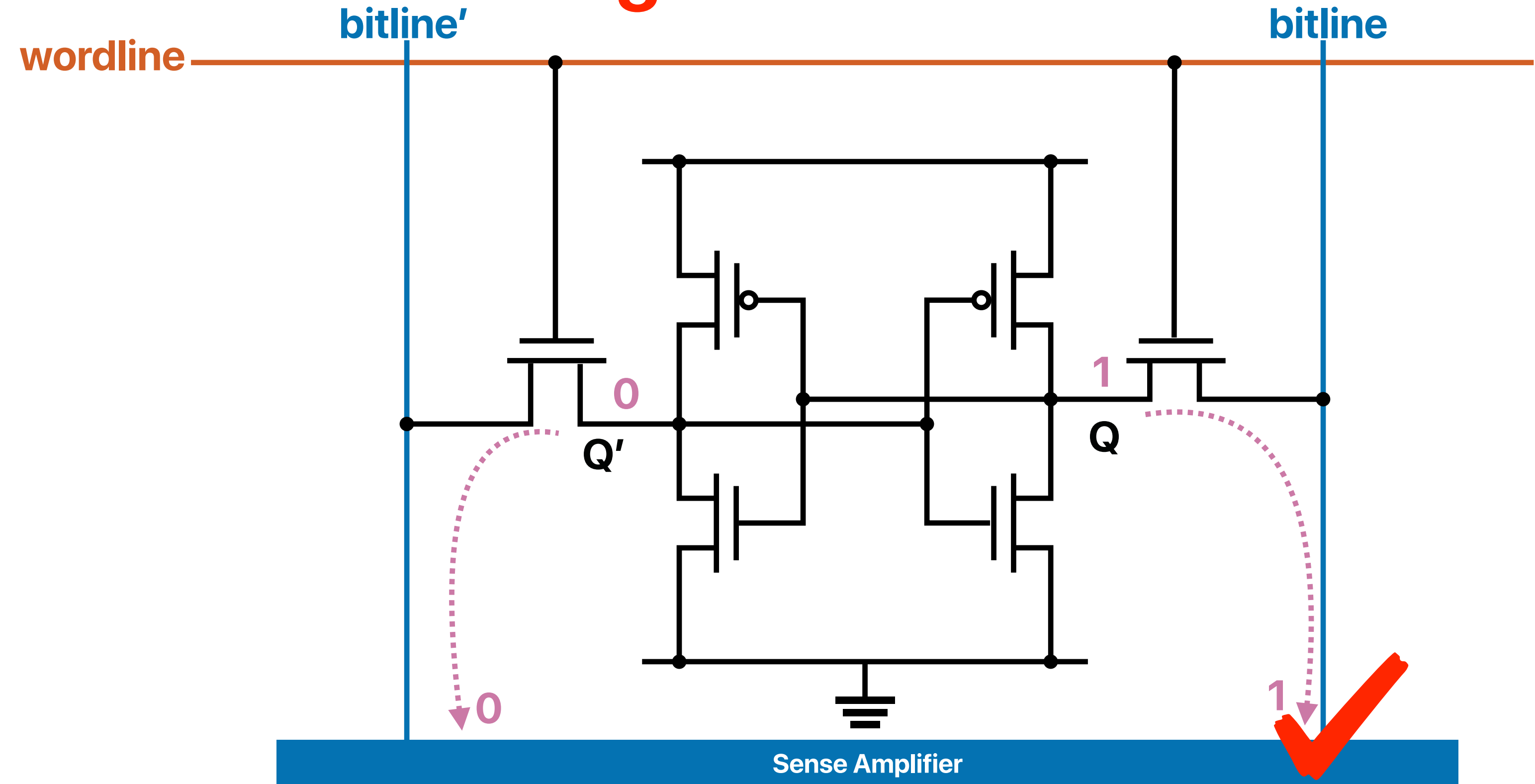
Write "1" to an SRAM Cell



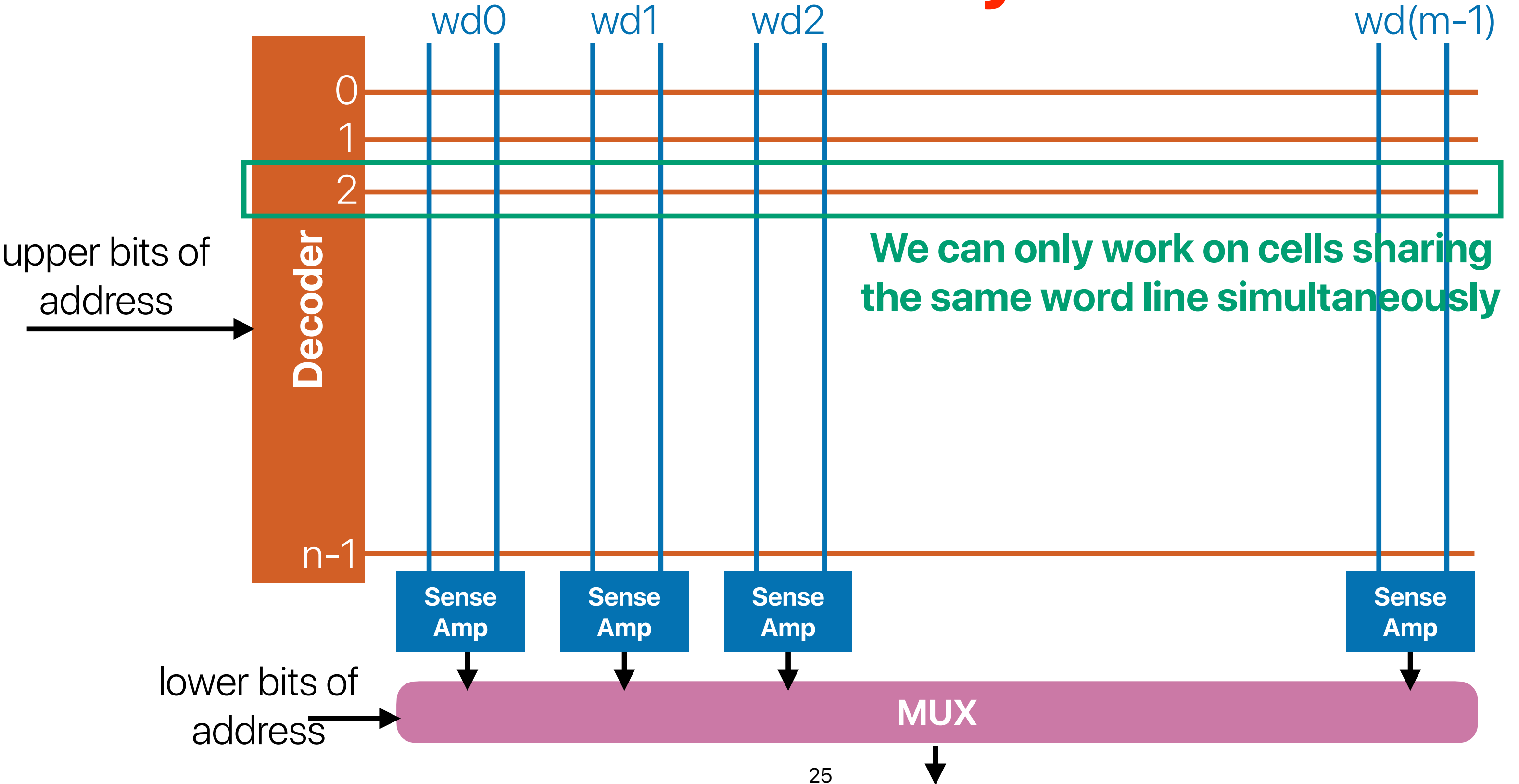
Write "0" to an SRAM Cell

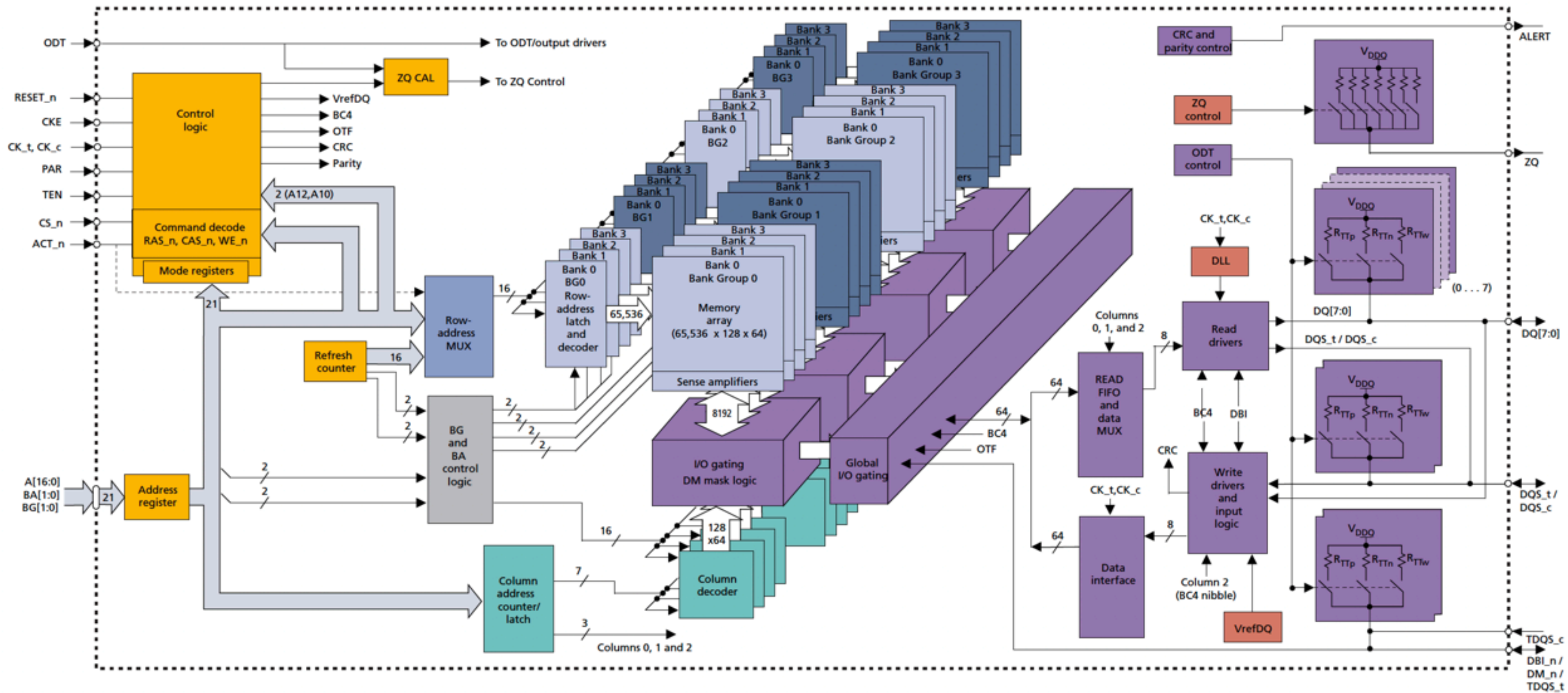


Reading from an SRAM Cell

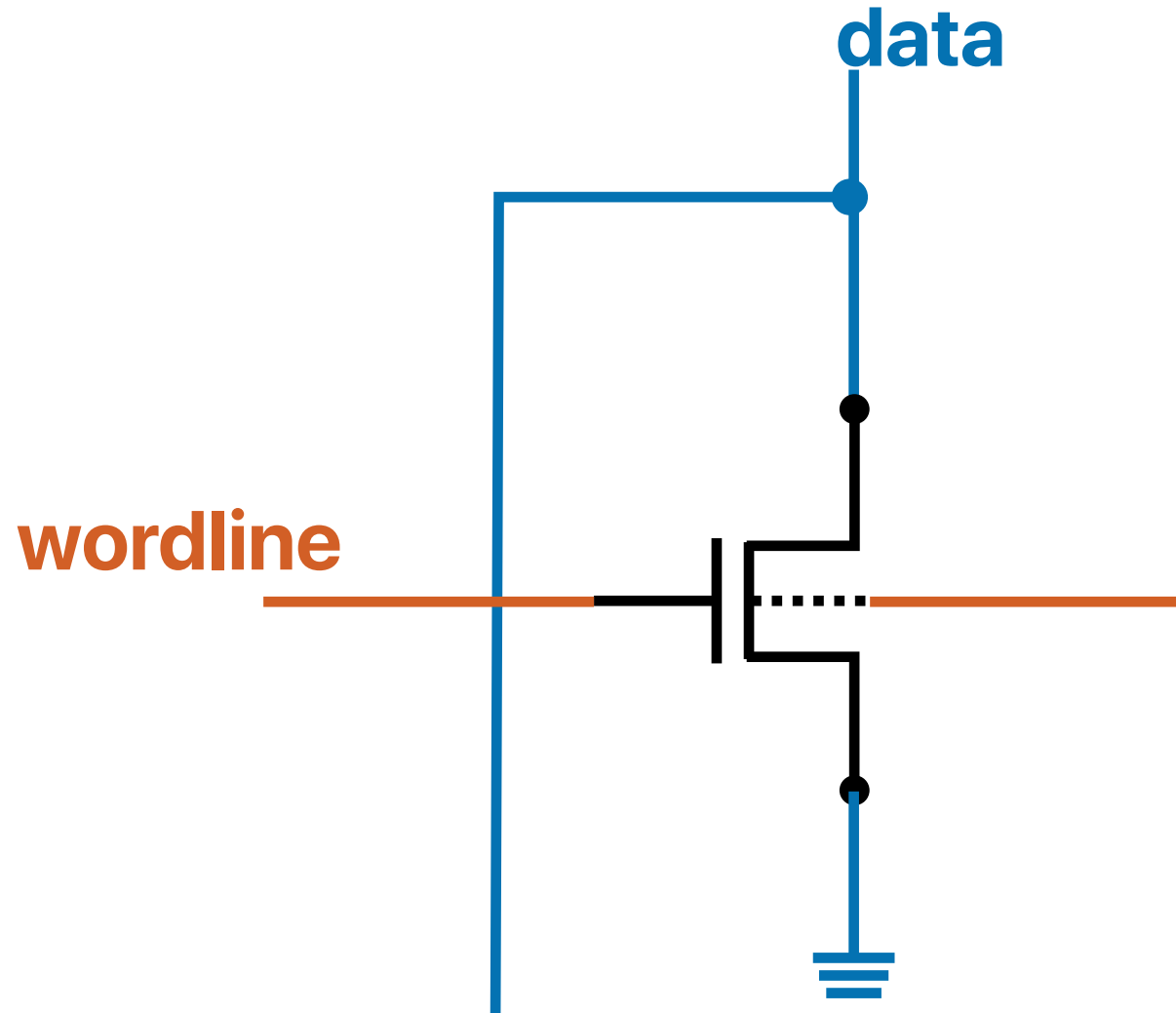


SRAM array

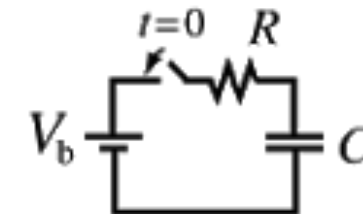




An DRAM cell



- 1 transistor (rather than 6)
- Relies on large capacitor to store bit
 - Write: transistor conducts, data voltage level gets stored on top plate of capacitor
 - Read: look at the value of data voltage



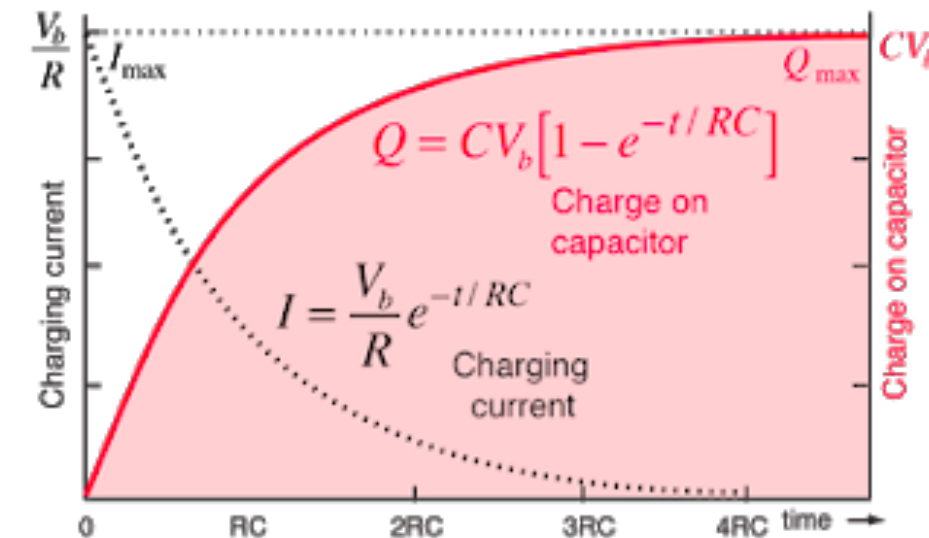
$$V_b = V_R + V_C$$

$$V_b = IR + \frac{Q}{C}$$

As charging progresses,

$$V_b = IR + \frac{Q}{C}$$

current decreases and charge increases.



At $t = 0$

$$Q = 0$$

$$V_C = 0$$

$$I = \frac{V_b}{R}$$

As $t \rightarrow \infty$

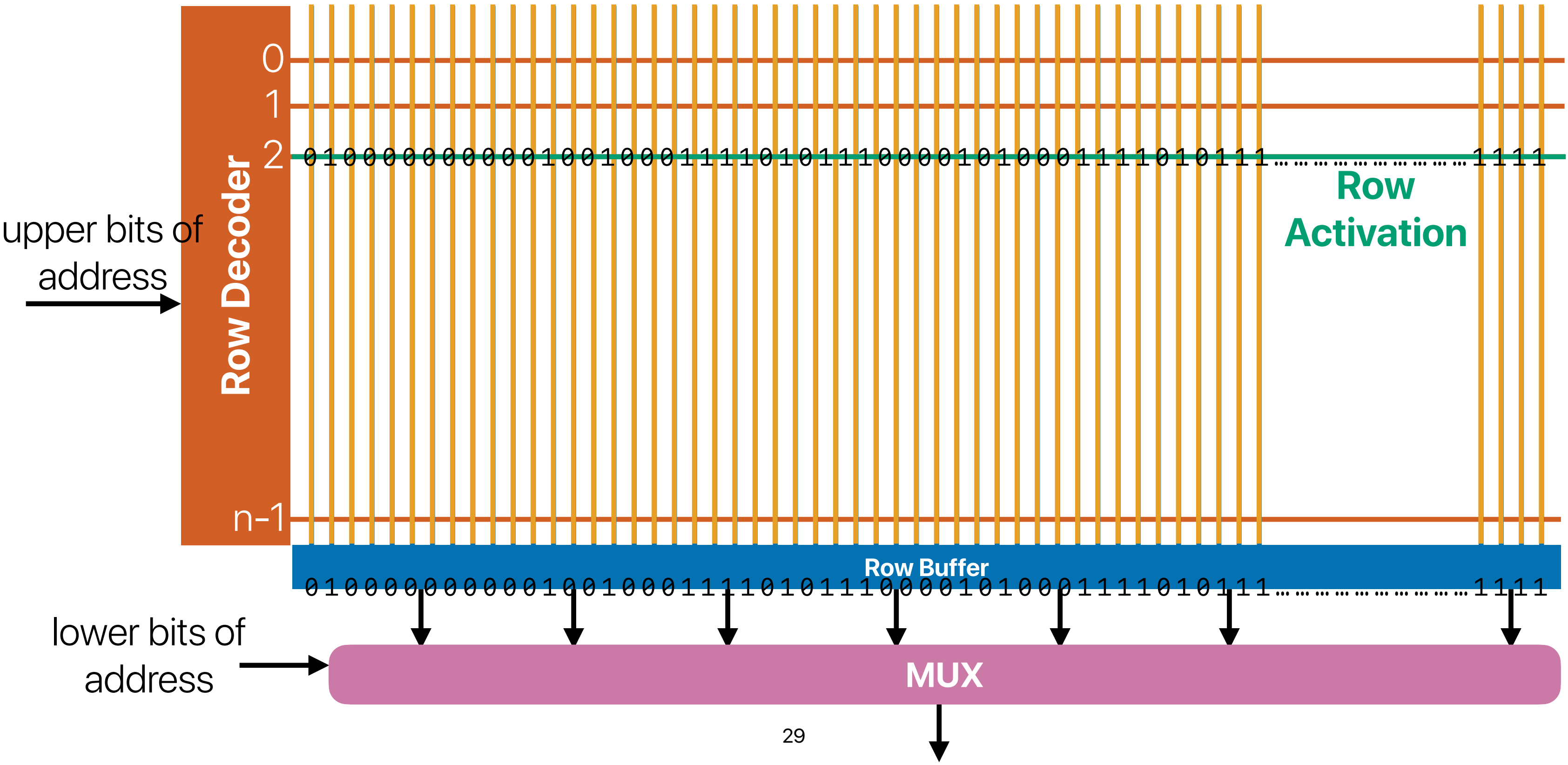
$$Q \rightarrow CV_b$$

$$V_C \rightarrow V_b$$

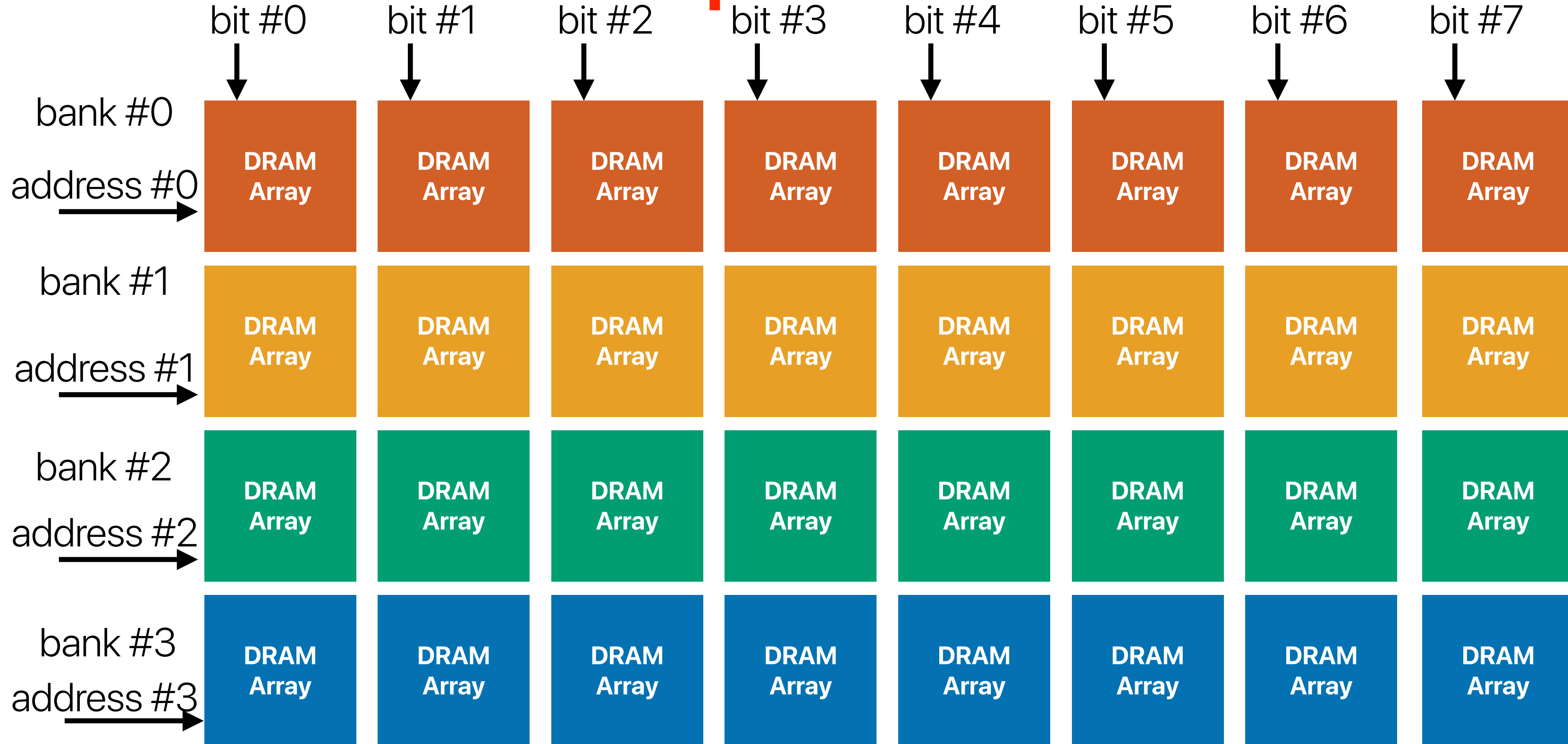
$$I \rightarrow 0$$

DRAM array

Bitline Precharge

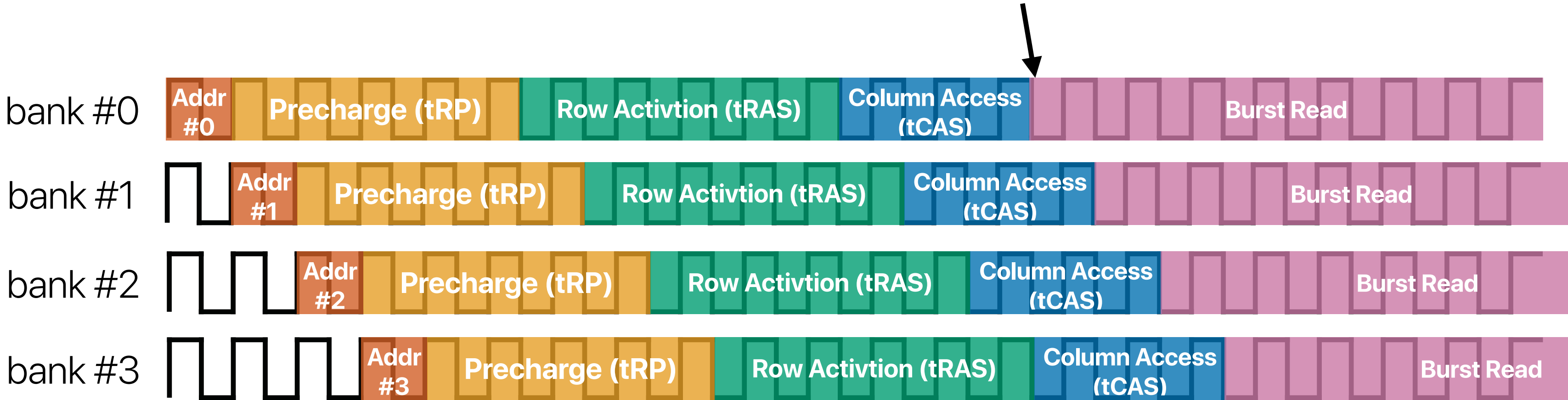


Multiple Banks



Multi-bank access

we can start output a "byte" from every 8 chips each cycle after this

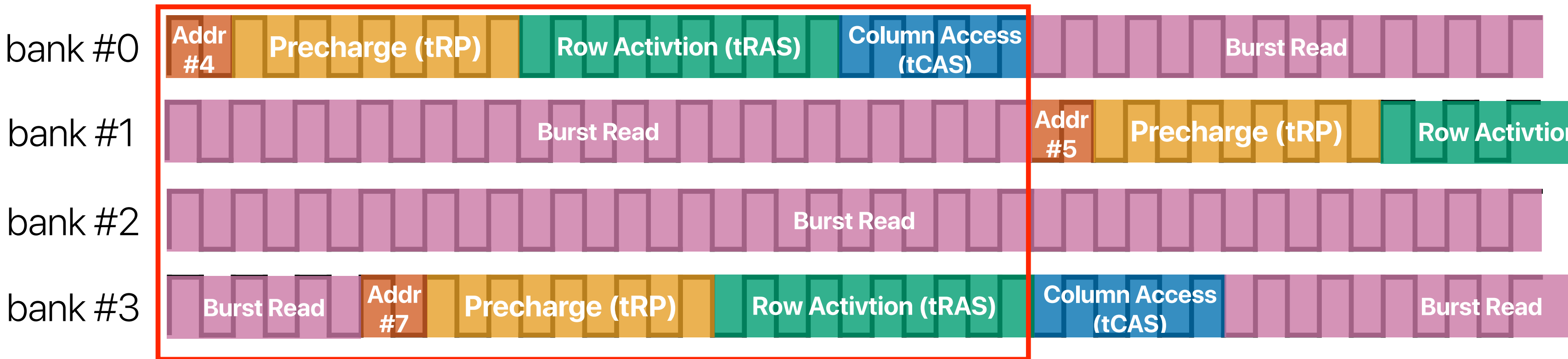


only one bank can accept request each cycle

the memory bandwidth
can be fully utilized after
this

Multi-bank access

The latency of pre-charge, row/column accesses is fully covered!



DRAM Performance

- Latency per "8-bit" — 0.75 ns (if it's row-buffered)

- Bandwidth per die = $\frac{1}{0.75ns} = 1.33GB/sec$

- 16 chips = $16 \times \frac{1}{0.75ns} = 21.33GB/sec$

2. Key Features

[Table 2] 8Gb DDR4 C-die Speed bins

Speed	DDR4-1600	DDR4-1866	DDR4-2133	DDR4-2400	DDR4-2666	Unit
	11-11-11	13-13-13	15-15-15	17-17-17	19-19-19	
tCK(min)	1.25	1.071	0.937	0.833	0.75	ns
CAS Latency	11	13	15	17	19	nCK
tRCD(min)	13.75	13.92	14.06	14.16	14.25	ns
tRP(min)	13.75	13.92	14.06	14.16	14.25	ns
tRAS(min)	35	34	33	32	32	ns
tRC(min)	48.75	47.92	47.06	46.16	46.25	ns

- JEDEC standard 1.2V (1.14V~1.26V)
- V_{DDQ} = 1.2V (1.14V~1.26V)
- V_{PP} = 2.5V (2.375V~2.75V)
- 800 MHz f_{CK} for 1600Mb/sec/pin, 933 MHz f_{CK} for 1866Mb/sec/pin, 1067MHz f_{CK} for 2133Mb/sec/pin, 1200MHz f_{CK} for 2400Mb/sec/pin, 1333MHz f_{CK} for 2666Mb/sec/pin
- 8 Banks (2 Bank Groups)
- Programmable CAS Latency (posted CAS): 10,11,12,13,14,15,16,17,18,19,20
- Programmable CAS Write Latency (CWL) = 9,11 (DDR4-1600), 10,12 (DDR4-1866),11,14 (DDR4-2133),12,16 (DDR4-2400) and 14,18 (DDR4-2666)
- 8-bit pre-fetch
- Burst Length: 8, 4 with tCCD = 4 which does not allow seamless read or write [either On the fly using A12 or MRS]
- Bi-directional Differential Data-Strobe
- Internal (self) calibration: Internal self calibration through ZQ pin (RZQ: 240 ohm ± 1%)
- On Die Termination using ODT pin
- Average Refresh Period 7.8us at lower than T_{CASE} 85°C, 3.9us at 85°C < T_{CASE} ≤ 95 °C
- Connectivity Test Mode (TEN) is Supported

The 8Gb DDR4 SDRAM C-die is organized as a 64Mbit x 16 I/Os x 8banks device. This synchronous device achieves high speed double-data-rate transfer rates of up to 2666Mb/sec/pin (DDR4-2666) for general applications.

The chip is designed to comply with the following key DDR4 SDRAM features such as posted CAS, Programmable CWL, Internal (Self) Calibration, On Die Termination using ODT pin and Asynchronous Reset.

All of the control and address inputs are synchronized with a pair of externally supplied differential clocks. Inputs are latched at the crosspoint of differential clocks (CK rising and \overline{CK} falling). All I/Os are synchronized with a pair of bidirectional strobes (DQS and \overline{DQS}) in a source synchronous fashion. The address bus is used to convey row, column, and bank address information in a RAS/CAS multiplexing style. The DDR4 device operates with a single 1.2V (1.14V~1.26V) power supply, 1.2V(1.14V~1.26V) V_{DDQ} and 2.5V (2.375V~2.75V) V_{PP}.

The 8Gb DDR4 C-die device is available in 96ball FBGAs(x16).

Google Claimed ideas

- Claimed ideas
 - Setup and benchmarking SmartSSDs
 - Parallel processing using matrix parallelism
 - Benchmarking fault-tolerant mechanisms in machine learning
 - Benchmarking and optimizing multimedia machine learning applications on heterogeneous computing resources
 - LLM on Edge TPUs/Embedded Systems
- Contact me if you've confirmed your project ideas but not seeing it in the slide — also send me your team member names
- Make an appointment through Google Calendar if you need consultant on projects

Google Other interesting ideas

- Can we use RT cores to accelerate other problems beyond identified ones?
- Can you improve the efficiency of existing problems on Tensor Cores (matrix decompositions, security algorithms)?
- Can you use other accelerated libraries (e.g., cuDNN, cuFFT) for applications beyond their domains?
- Can you think about some data representations that can make important compute kernels (e.g., machine learning algorithms, matrix multiplications) more efficient or secure?

Google Project Presentations

- Make an appointment on 2/1 and 2/6 through the Google Calendar
- 12 minute presentation with 3 minute Q & A
- Why & what & how!!! — considering you're giving a presentation at Apple's keynote
 - 6-minute why — why should everyone care about this problem? Why is this still a problem?
 - 4-minute what — what are you proposing in this project to address the problem?
 - 2-minute how — expected platforms/engineering efforts, milestones and workload distribution among members
 - Please reference this article to make a good presentation <https://cseweb.ucsd.edu/~swanson/GivingTalks.html>

Electrical Computer Science Engineering

277

つくづく

