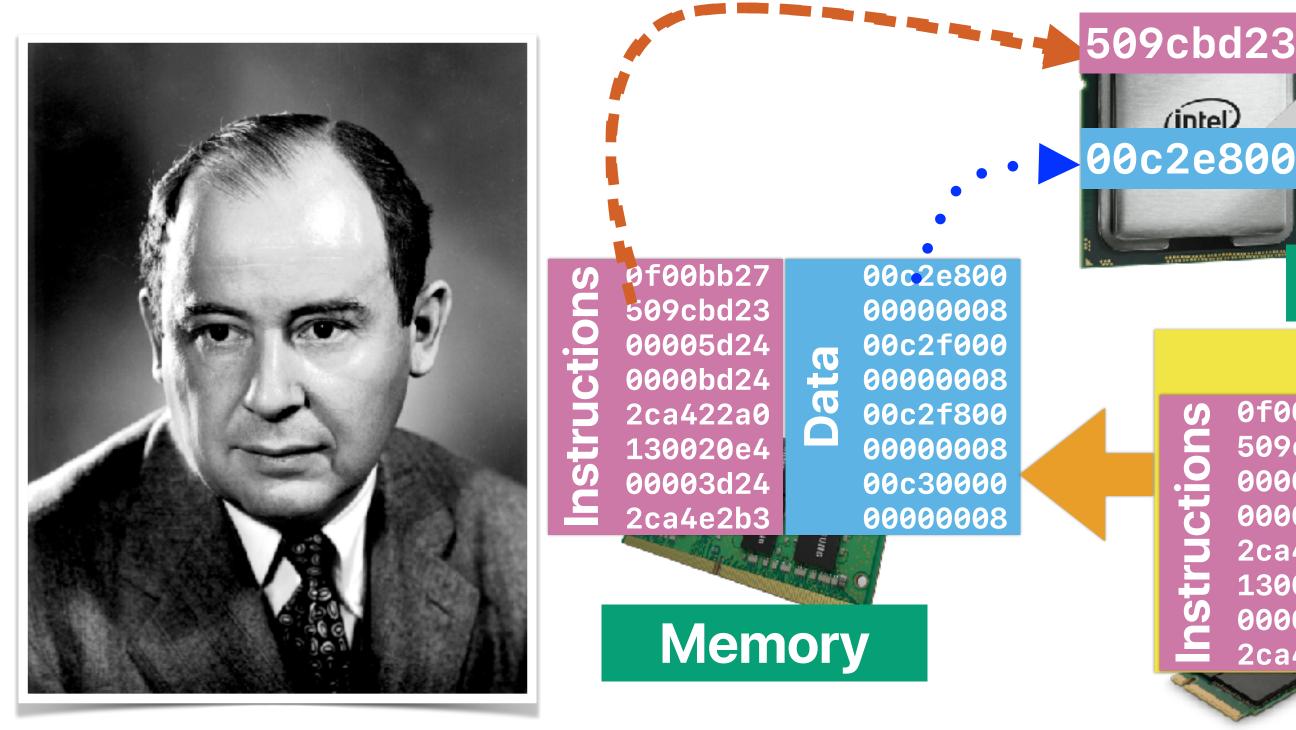
# Performance (4) & Memory Hierarchy (1)

Hung-Wei Tseng



# von Neuman Architecture





### 509cbd23 (intel)

### Processor

### Program

ANDA

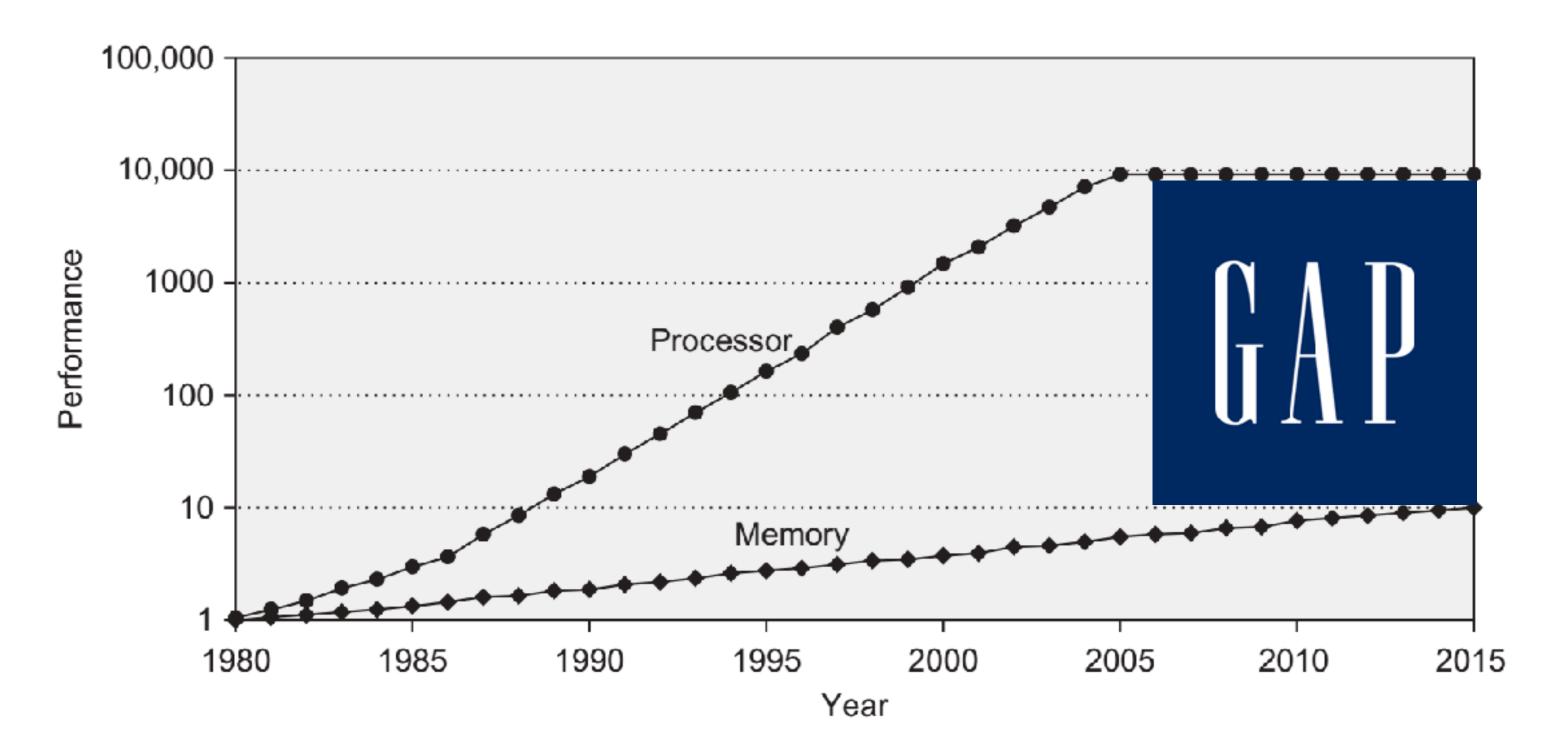
Instructions

0f00bb27 509cbd23 00005d24 0000bd24 2ca422a0 130020e4 00003d24 2ca4e2b3

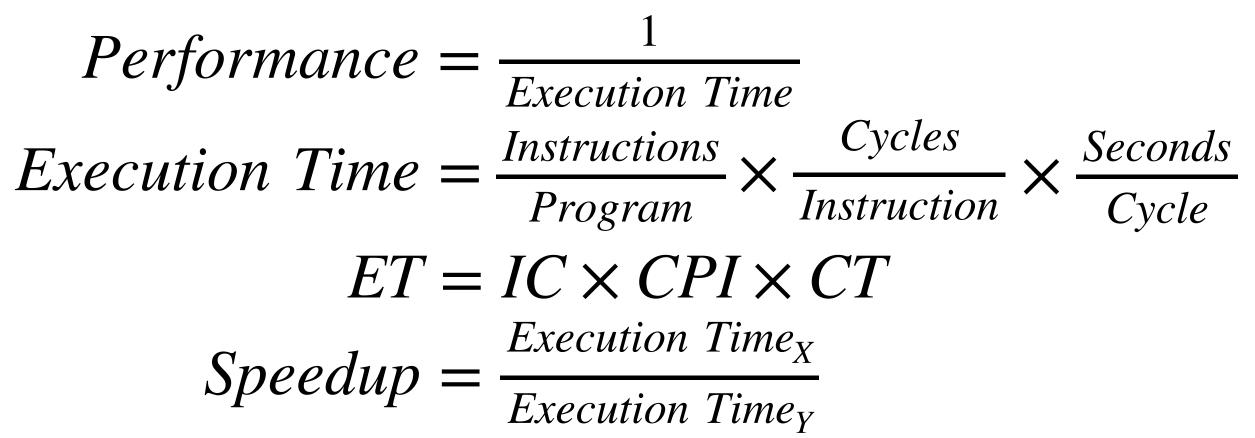
00c2e800 80000008 00c2f000 ta 00000008 **D** 00c2f800 80000008 00c30000 80000008 :10

Storage

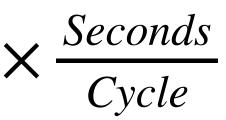
### **Recap: Performance gap between Processor/Memory**



# **Recap: Summary of CPU Performance Equation**



- IC (Instruction Count)
  - ISA, Compiler, algorithm, programming language, programmer
- CPI (Cycles Per Instruction)
  - Machine Implementation, microarchitecture, compiler, application, algorithm, programming language, programmer
- Cycle Time (Seconds Per Cycle)
  - Process Technology, microarchitecture, programmer



# Amdahl's Law

$$Speedup_{enhanced}(f, s) = \frac{1}{(1-f)}$$

- Corollary #1: Maximum speedup
- Corollary #2: Make the common case fast
  - Common case changes all the time
- Corollary #3: Single-core performance  $S_{peedup_{parallel}}(f_p)$ still matters
- Corollary #4: Exploiting more parallelism from a program is the key to performance gain in modern architectures  $Speedup_{parallel}(f_p)$

se fast  $Speedup_{max}(f, \infty) = \frac{1}{(1-f_1)}$   $Speedup_{max}(f_1, \infty) = \frac{1}{(1-f_1)}$   $Speedup_{max}(f_2, \infty) = \frac{1}{(1-f_2)}$   $Speedup_{max}(f_3, \infty) = \frac{1}{(1-f_3)}$   $Speedup_{max}(f_4, \infty) = \frac{1}{(1-f_4)}$   $Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1-f_{parallelizable})}$ 

arallelizable, 
$$\infty$$
) =  $\frac{1}{(1 - f_{parallelizable})}$ 

### Is TFLOPS (Tera FLoating-point Operations Per Second) a good metric?

 $TFLOPS = \frac{\# of floating point instructions \times 10^{-12}}{Exection Time}$ 

 $IC \times \%$  of floating point instructions  $\times 10^{-12}$ 

 $IC \times CPI \times CT$ 

% of floating point instructions  $\times 10^{-12}$  **IC is gone!** CPI  $\times$  CT

### A good performance metric must cover IC, CPI, CT!

- Cannot compare different ISA/compiler
  - What if the compiler can generate code with fewer instructions?
  - What if new architecture has more IC but also lower CPI?
- Does not make sense if the application is not floating point intensive

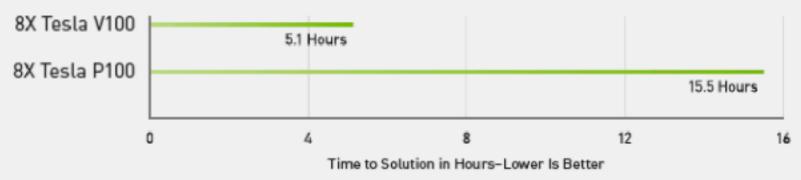




- How to make "fair comparisons" or ... how to fool others with performance metrics
- The Basic Idea behind Memory Hierarchy
- How cache works

				🗎 nvidia.com		¢]
וועח 📀	DIA.~					
	icial Intelligence Computing Leadership from N D & DATA CENTER	PRODUCTS -	SOLUTIONS	▼ APPS		EVELOPERS
Tesla V1	00				AI TRAINING	AI INFERENCE

### Deep Learning Training in Less Than a Workday



Server Config: Dual Xeon E5-2699 v4 2.6 GHz | 8X NVIDIA® Tesla® P100 or V100 | ResNet-50 Training on MXNet for 90 Epochs with 1.28M ImageNet Dataset.

### **AI TRAINING**

From recognizing speech to training virtual personal assistants and teaching autonomous cars to drive, data scientists are taking on increasingly complex challenges with AI. Solving these kinds of problems requires training deep learning models that are exponentially growing in complexity, in a practical amount of time.

With 640 Tensor Cores, Tesla V100 is the world's first GPU to break the 100 teraFLOPS (TFLOPS) barrier of deep learning performance. The next generation of NVIDIA NVLink<sup>™</sup> connects multiple V100 GPUs at up to 300 GB/s to create the world's most powerful computing servers. AI models that would consume weeks of computing resources on previous systems can now be trained in a few days. With this dramatic reduction in training time, a whole new world of problems will now be solvable with AI.

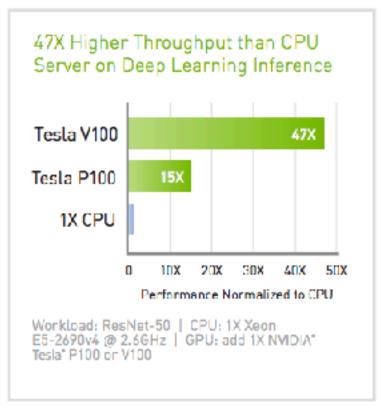


### TECHNOLOGIES -

### E HPC DATA CENTER GPUS SPECIFICATIONS

### The Most Advanced Data Center GPU Ever Built.

NVIDIA® Tesla® V100 is the world's most advanced data center. GPU ever built to accelerate AI, HPC, and graphics. Powered by NVIDIA Volta, the latest GPU architecture, Tesla V100 offers the performance of up to 100 CPUs in a single GPU—enabling data scientists, researchers, and engineers to tackle challenges that were once thought impossible.





### 1 GPU Node Replaces Up To 54 CPU Nodes Node Replacement: HPC Mixed Workload

Max Power

### SPECIFICATIONS



Tesla V100 PCle



### Tesla V100 SXM2

GPU Architecture	NVIDIA Volta		
NVIDIA Tensor Cores	640		
NVIDIA CUDA <sup>®</sup> Cores	5,120		
Double-Precision Performance	7 TFLOPS	7.8 TFLOPS	
Single-Precision Performance	14 TFLOPS	15.7 TFLOPS	
Tensor Performance	112 TFLOPS	125 TFLOPS	
GPU Memory	32GB /16GB HBM2		
Memory	0000	D/ana	

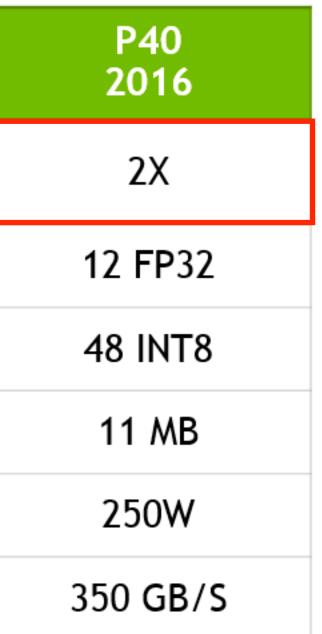
### 900GB/sec

	Yes		
	32GB/sec	300GB/sec	
face	PCIe Gen3	NVIDIA NVLink	
	PCIe Full Height/Length	SXM2	

# They try to tell it's the better Al hardware

https://blogs.nvidia.com/blog/2017/04/10/ai-drives-rise-accelerated-computing-datacenter/

	K80 2012	TPU 2015
Inferences/Sec <10ms latency	1/ <sub>13</sub> X	1X
Training TOPS	6 FP32	NA
Inference TOPS	6 FP32	90 INT8
<b>On-chip Memory</b>	16 MB	24 MB
Power	300W	75W
Bandwidth	320 GB/S	34 GB/S



Ins	stance	s per batch	Inferer	<b>ice per s</b>	econc
_	erences econd	= Inferences Operation	$\times \frac{Operations}{Second}$		
		$= \frac{Inferences}{Operation}$	$\times \left[ \frac{operations}{cycle} \right]$	$\times \frac{cycles}{second} \times \#_{-}$	_of_PEs :
				Hardware	Model
		Operations per inf	erence		V
		Operations per o	cycle	V	
		Cycles per sec	ond	V	
		Number of P	Es	V	
		Utilization of F	PEs	V	V
	Effectu	al operations out of (	(total) operations		V
	Effectual	operations plus unex operations per o		V	



### × Utilization\_of\_PEs]

Input Data

# What's wrong with inferences per second?

- There is no standard on how they inference but these affect!
  - What model?
  - What dataset?
- That's why Facebook is trying to promote an AI benchmark **MLPerf** ٠

is an inaccurate summary performance metric. Our results show that IPS is a poor overall performance summary for NN hardware, as it's simply the inverse of the complexity of the typical inference in the application (e.g., the number, size, and type of NN layers). For example, the TPU runs the 4-layer MLP1 at 360,000 IPS but the 89-layer CNN1 at only 4,700 IPS, so TPU IPS vary by 75X! Thus, using IPS as the single-speed summary is even more misleading for NN accelerators than MIPS or FLOPS are for regular processors [23], so IPS should be even more disparaged. To compare NN machines better, we need a benchmark suite written at a high-level to port it to the wide variety of NN architectures. Fathom is a promising new attempt at such a benchmark suite [3].

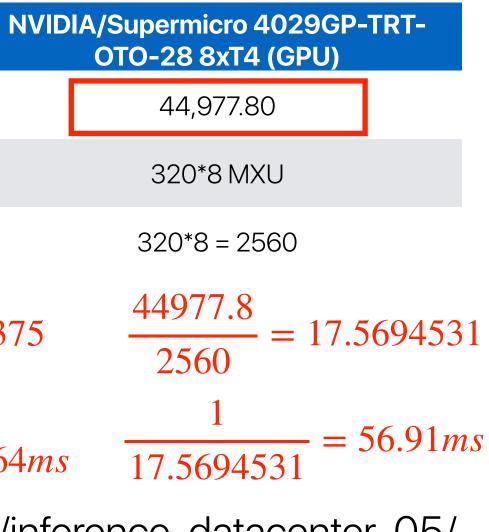
Pitfall: For NN hardware, Inferences Per Second (IPS)

# **ImageNet Performance**

operation. Ideally, the camera-to-recognition latency per frame should not substantially exceed the inter-frame time of the input images (e.g., 25 milliseconds for a 40 FPS camera).

	Intel <sup>®</sup> Xeon <sup>®</sup> Platinum 9200 processors (CPU)	Google Cloud TPU v3 (TPU)	1
Inferences per second	5,965.62	32,716.00	
Cores	112 processors * 2-way SMT	2 MXU	
Number of Maximum Parallel Inferencing Instances	224	2x256	
	$\frac{5965.62}{224} = 26.63$	$\frac{32716}{2} = 63.89843$	37
		$\frac{1}{0.0156498349} = 15.0$ mlcommons.org/en	

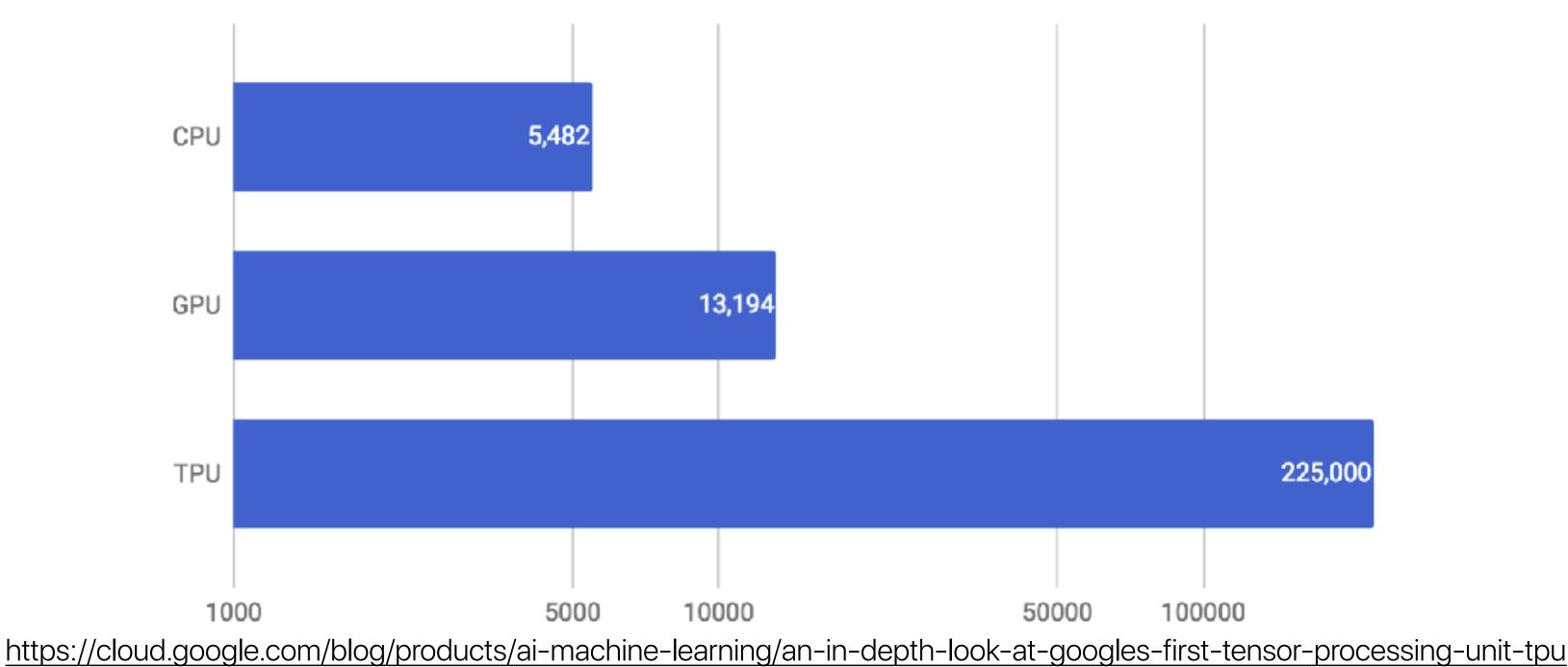




/inference-datacenter-05/

# **IPS with strict 7ms limitation**

Predictions per sec





### 225,000

## 100000

# Choose the right metric — Latency v.s. Throughput/Bandwidth

# Latency v.s. Bandwidth/Throughput

- Latency the amount of time to finish an operation
  - Access time
  - Response time
- Throughput the amount of work can be done within a given period of time
  - Bandwidth (MB/Sec, GB/Sec, Mbps, Gbps)
  - IOPs (I/O operations per second)
  - FLOPs (Floating-point operations per second)
  - IPS (Inferences per second)





### **Squid Game**

2021 | TV-MA | 1 Season | TV Thrillers

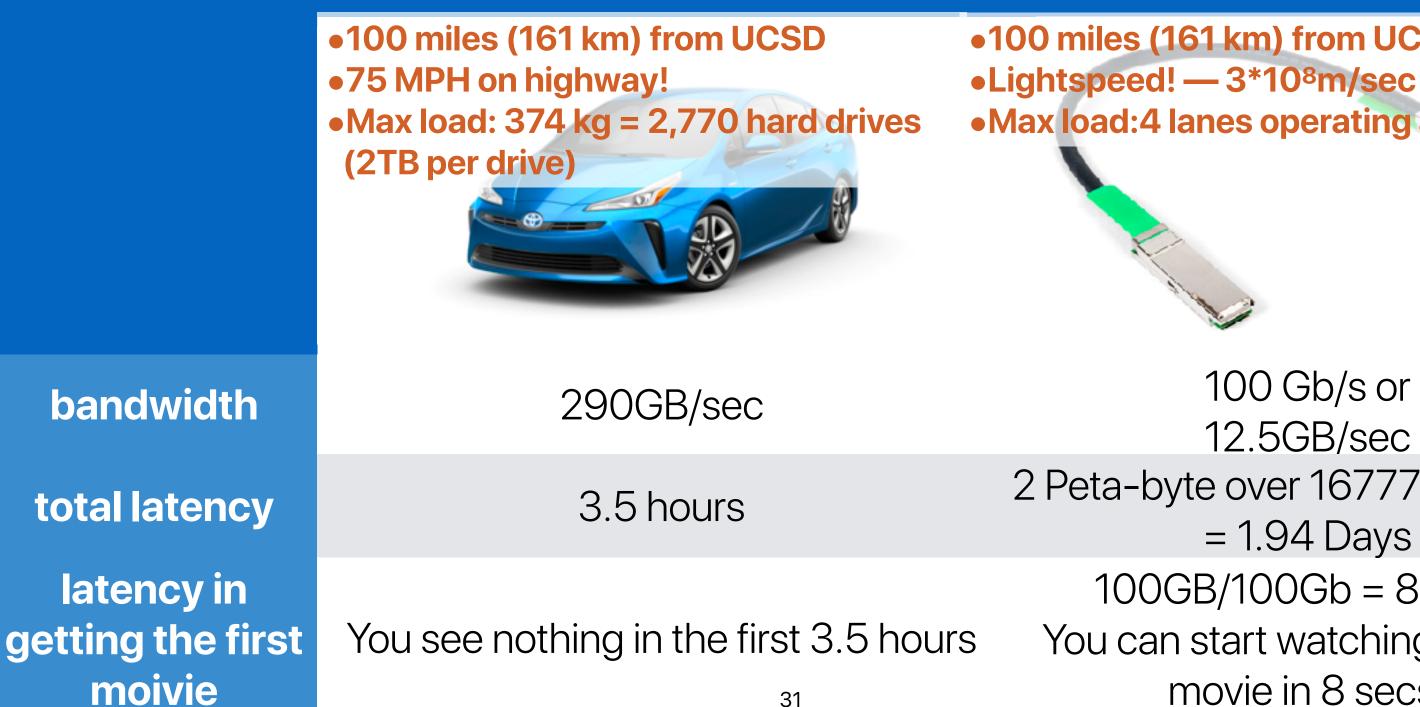
Hundreds of cash-strapped players accept a strange invitation to compete in children's games. Inside, a tempting prize awaits — with deadly high stakes.

Starring: Lee Jung-jae, Park Hae-soo, Wi Ha-jun Creators: Hwang Dong-hyuk



# Latency/Delay v.s. Throughput





### 100 Gb Network

### 100 miles (161 km) from UCSD •Max load:4 lanes operating at 25GHz

### 100 Gb/s or 12.5GB/sec 2 Peta-byte over 167772 seconds = 1.94 Days100GB/100Gb = 8 secs!You can start watching the first movie in 8 secs!



# **Extreme Multitasking Performance**

- Dual 4K external monitors
- 1080p device display
- 7 applications

# What's missing in this video clip?

- The ISA of the "competitor"
- Clock rate, CPU architecture, cache size, how many cores
- How big the RAM?
- How fast the disk?



### 12 ways to Fool the Masses When Giving Performance Results on Parallel Computers

- Quote only 32-bit performance results, not 64-bit results.
- Present performance figures for an inner kernel, and then represent these figures as the performance of the entire application.
- Quietly employ assembly code and other low-level language constructs.
- Scale up the problem size with the number of processors, but omit any mention of this fact.
- Quote performance results projected to a full system.
- Compare your results against scalar, unoptimized code on Crays.
- When direct run time comparisons are required, compare with an old code on an obsolete system.
- If MFLOPS rates must be quoted, base the operation count on the parallel implementation, not on the best sequential implementation.
- Quote performance in terms of processor utilization, parallel speedups or MFLOPS per dollar.
- Mutilate the algorithm used in the parallel implementation to match the architecture.
- Measure parallel run times on a dedicated system, but measure conventional run times in a busy environment.
- If all else fails, show pretty pictures and animated videos, and don't talk about performance.

- e on an obsolete system. I implementation, not on
- <sup>.</sup> MFLOPS per dollar. rchitecture. onal run times in a busy

# Performance of modern DRAM

			Best case access time (no precharge)			Precharge needed	
Production year	Chip size	DRAM type	RAS time (ns)	CAS time (ns)	Total (ns)	Total (ns)	
2000	256M bit	DDR1	21	21	42	63	
2002	512M bit	DDR1	15	15	30	45	
2004	1G bit	DDR2	15	15	30	45	
2006	2G bit	DDR2	10	10	20	30	
2010	4G bit	DDR3	13	13	26	39	
2016	8G bit	DDR4	13	13	26	39	

Figure 2.4 Capacity and access times for DDR SDRAMs by year of production. Access time is for a random memory word and assumes a new row must be opened. If the row is in a different bank, we assume the bank is precharged; if the row is not open, then a precharge is required, and the access time is longer. As the number of banks has increased, the ability to hide the precharge time has also increased. DDR4 SDRAMs were initially expected in 2014, but did not begin production until early 2016.



# https://www.pollev.com/hungweitseng close in 1:30

# The impact of "slow" memory

- Assume that we have a processor running @ 2 GHz and a program with 30% of load/store instructions. If the computer has "perfect" memory, the CPI is just 1. Now, consider we have DDR4 and the program is well-behaved that precharge is never necessary — the access latency is simply 26 ns. What's the average CPI (pick the most close one)?
  - A. 9
  - B. 17
  - C. 27
  - D. 35
  - E. 69

Е

B

A

# The impact of "slow" memory

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  - A. 9
  - B. 17
  - C. 27
  - D. 35

E. 69

### $1 + 100\% \times (52) + 30\% \times 52 = 68.6$ cycles



# **Alternatives?**

Memory technology	Typical access time
SRAM semiconductor memory	0.5–2.5ns
DRAM semiconductor memory	50–70ns
Flash semiconductor memory	5,000-50,000ns
Magnetic disk	5,000,000-20,000,000ns
	<b>Fast, but expensive</b>

### **\$ per GiB in 2012**

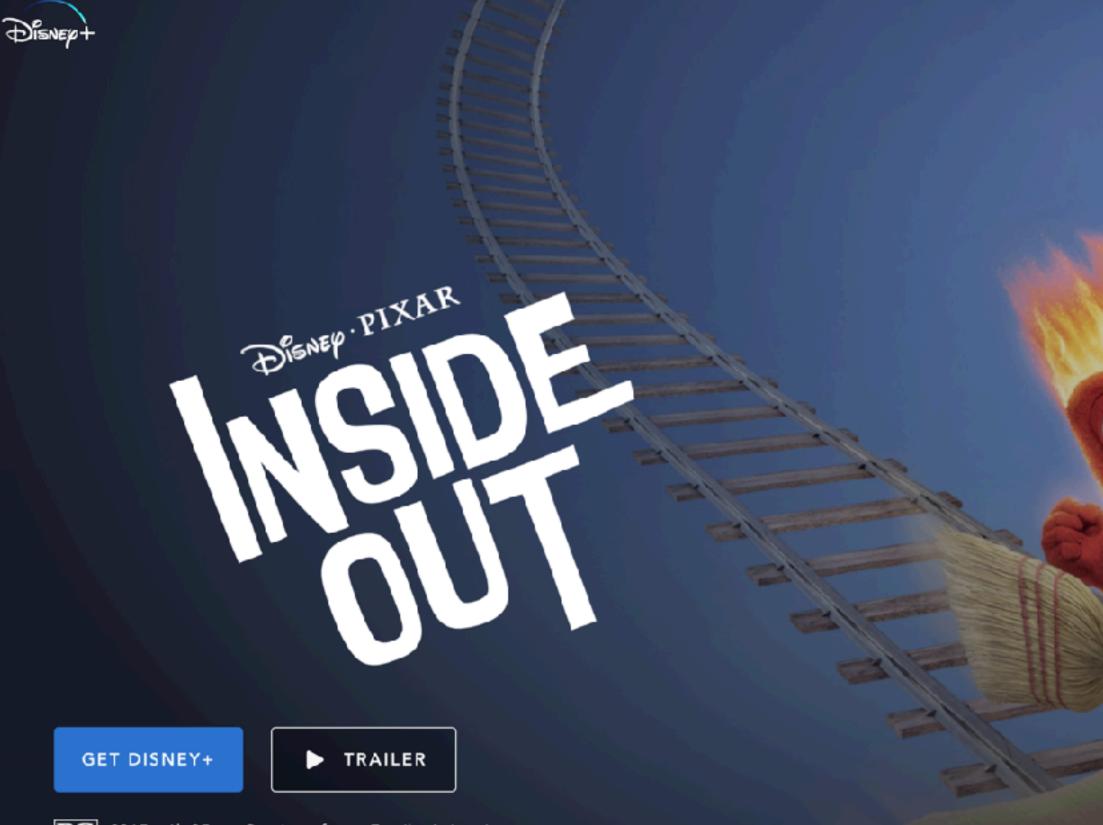
### \$500-\$1000

### \$10-\$20

### \$0.75-\$1.00

### \$0.05-\$0.10

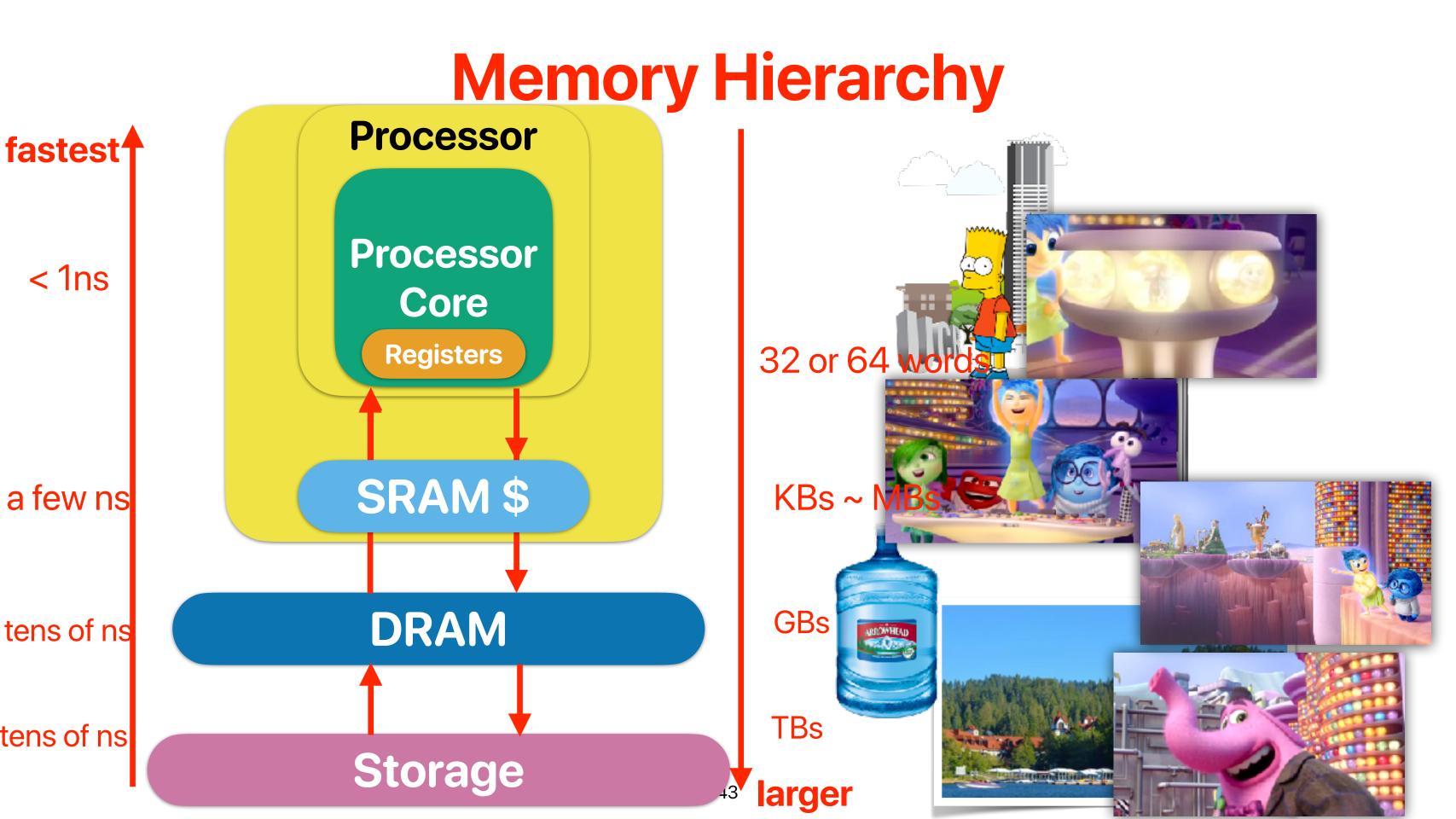
### e \$\$\$



**PG** 2015 • 1h 35m • Coming of age, Family, Animation

When 11-year-old Riley moves to a new city, her Emotions team up to help her through the transition. Joy, Fear, Anger, Disgust and Sadness work together, but when Joy and Sadness get lost, they must journey through unfamiliar places to get back home.



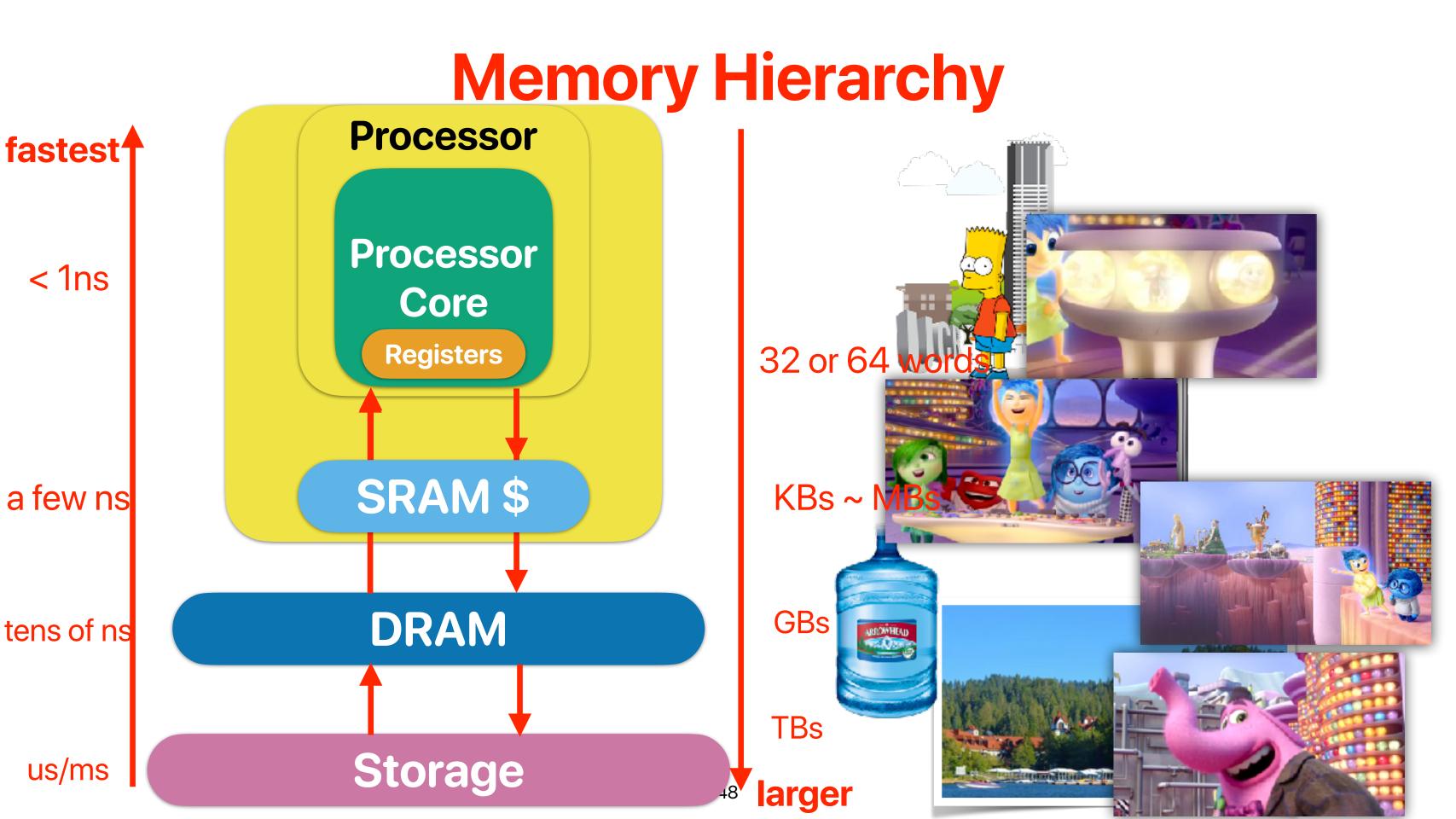


### https://www.pollev.com/hungweitseng close in 1:30 How can memory hierarchy help in performance?

- Assume that we have a processor running @ 2 GHz and a program with 30% of load/store instructions. If the computer has "perfect" memory, the CPI is just 1. Now, in addition to DDR4, whose latency 26 ns, we also got an SRAM cache with latency of just at 0.5ns and can capture 90% of the desired data/instructions. what's the average CPI (pick the most close one)?
  - A. 2
  - B. 4
  - C. 8
  - D. 16
  - E. 32

Е

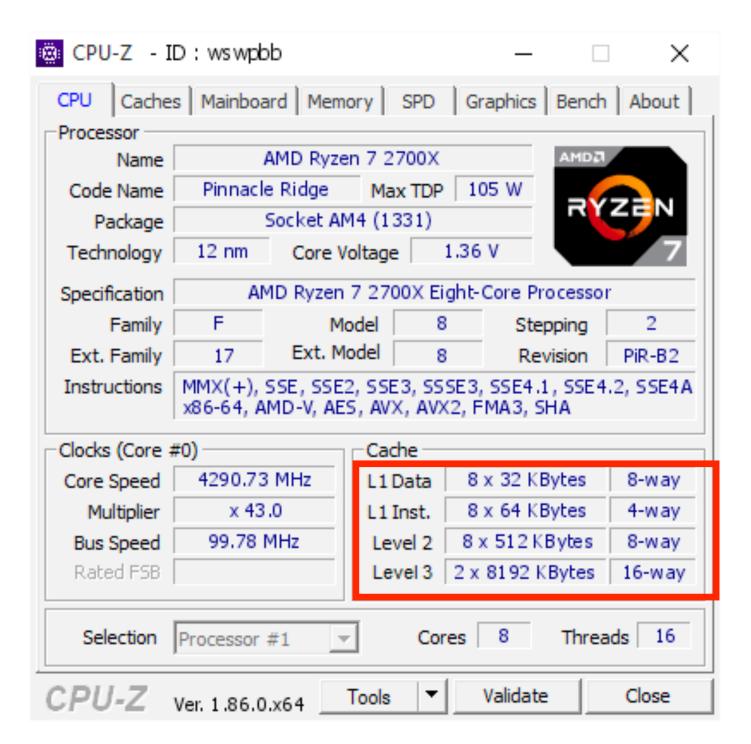
А



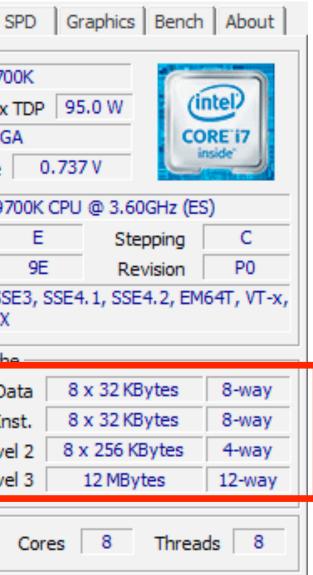
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  - A. 2
  - B. 4
  - $1 + (1 90\%) \times [100\% \times (52) + 30\% \times 52] = 7.76 \ cycles$ C. 8
    - D. 16
    - E. 32

# L1? L2? L3?



CPU Cache	s Mainboa	ard Memo	ory S
Processor			
Name		Intel Core	e i7 970
Code Name	Coffee Lake		Max
Package		Socket 1	151 LG
Technology	14 nm	Core V	oltage
Specification	In	tel® Core	™ i7-97
Family	6	Mo	odel
Ext. Family	6	Ext. Model	
Instructions	MMX, SSE, AES, AVX,		
Clocks (Core	#0)		-Cach
Core Speed	4798.85	5 MHz	L1D
Multiplier	x 48.0 (8 - 49)		L1 In
Bus Speed	99.98 MHz		Leve
Rated FSB			Leve
Selection	Socket #1	Ŧ	



### How can deeper memory hierarchy help in performance?

- Assume that we have a processor running @ 2 GHz and a program with 30% of load/store instructions. If the computer has "perfect" memory, the CPI is just 1. Now, in addition to DDR4, whose latency 26 ns, we also got a 2-level SRAM caches with
  - it's 1st-level one at latency of 0.5ns and can capture 90% of the desired data/ instructions.
  - the 2nd-level at latency of 5ns and can capture 60% of the desired data/instructions

What's the average CPI (pick the most close one)?

A. 2	÷.	1
B. 4		
C. 8		
D. 16		
E. 32		

### https://www.pollev.com/hungweitseng close in 1:30

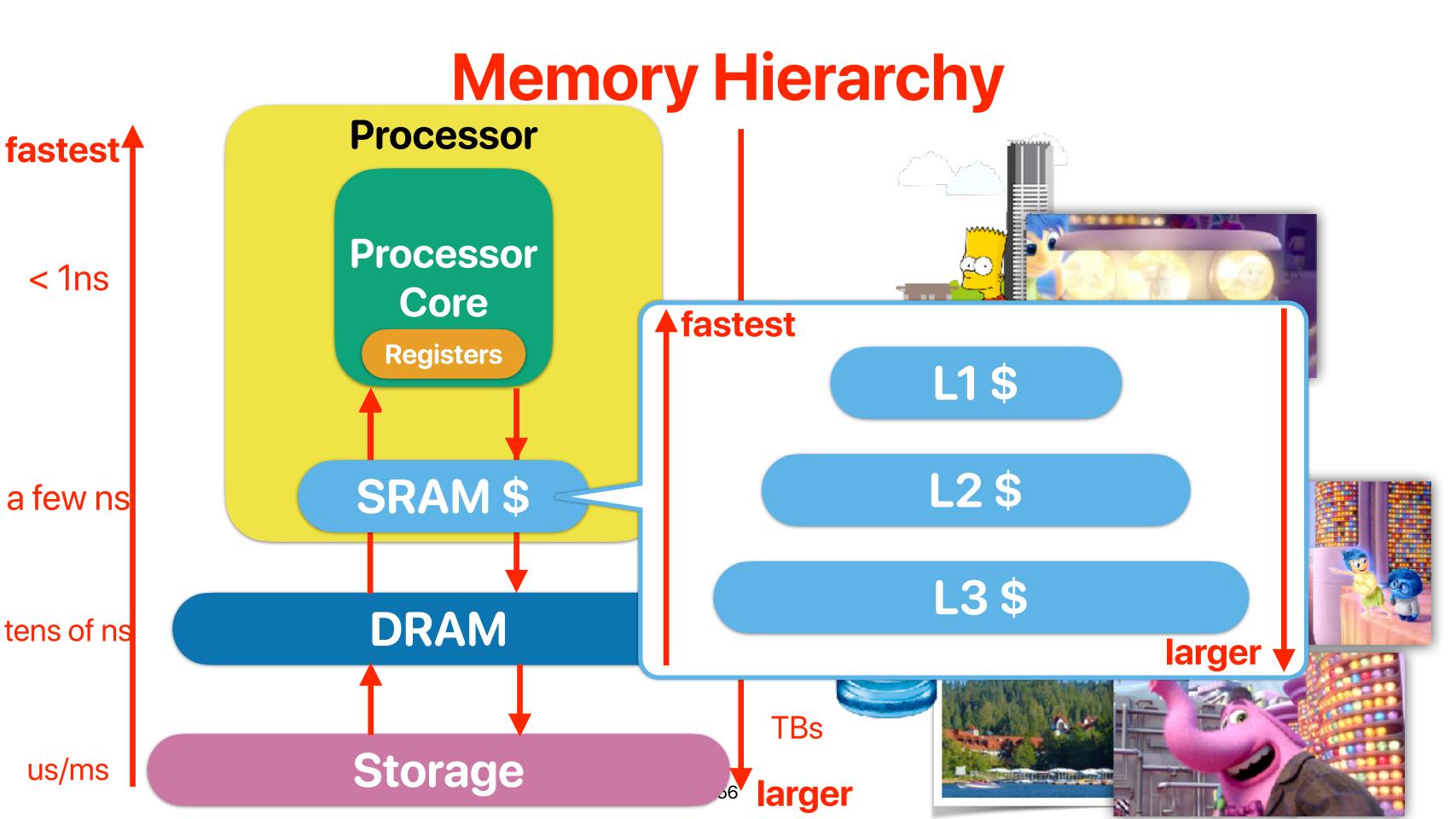
Е

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  - the 2nd-level at latency of 5ns and can capture 60% of the desired data/instructions What's the average CPI (pick the most close one)?

A. 2 B. 4  $1 + (1 - 90\%) \times [10 + (1 - 60\%) \times 52 + 30\% \times (10 + (1 - 60\%) \times 52)] = 5 cycles$ C. 8 D. 16

E. 32



# Why adding small SRAMs would work?

# Locality

 Which description about locality of arrays sum and A in the following code is the most accurate? for(i = 0; i < 100000; i++)

{ sum[i%10] += A[i]; }

- A. Access of A has temporal locality, sum has spatial locality
- B. Both A and sum have temporal locality, and sum also has spatial locality
- C. Access of A has spatial locality, sum has temporal locality
- D. Both A and sum have spatial locality
- E. Both A and sum have spatial locality, and sum also has temporal locality

### https://www.pollev.com/hungweitseng close in 1:30



 Which description about locality of arrays sum and A in the following code is the most accurate?

for(i = 0; i < 100000; i++){ sum[i%10] += A[i];

}

- spatial locality: A[0], A[1], A[2], A[3], .... sum[0], sum[1], ..., sum[9]
- temporal locality:

- reuse of sum[0], sum[1], ..., sum[9] A. Access of A has temporal locality, sum has spatial locality
- B. Both A and sum have temporal locality, and sum also has spatial locality
- C. Access of A has spatial locality, sum has temporal locality
- D. Both A and sum have spatial locality
- E. Both A and sum have spatial locality, and sum also has temporal locality



- Spatial locality application tends to visit nearby stuffs in the memory
  - Code the current instruction, and then PC + 4

# Most of time, your program is just visiting a very small amount of data/instructions within Code — loops, freque given window

Data — the same data can be read/write many times

# Announcement

- Assignment #1 due this Wednesday
  - Assignments SHOULD BE done/submitted individually if discussed with others, make sure their names on your submission
  - We will drop your least performing assignment as well
- Office Hours
  - Walk-in, no appointment is necessary
  - Hung-Wei/Prof. Usagi: MTu 2p-3p (WCH 406 or on Zoom)
  - Abenezer Wudenhe: WTh 3p-4p (Zoom only)

Computer Science & Engineering





