# Storage Systems and why should you care! )

Animesh Trivedi https://animeshtrivedi.github.io/

# **Briefly: Who am I?**

Assistant Professor (tenure-track)

#### Research: / like to build stuff

- Storage, networking, distributed, operating systems
- Design, implement, and deploy code and measure

#### **Teaching:**

- Advanced Network Programming (XB\_0048), **Storage Systems (XM\_0092)**, Systems Seminar (X\_405022)
- <u>https://animeshtrivedi.github.io/teaching/</u> (course material available openly)

#### **Outside computers**:

• Cycling, running, reading non-fiction - *talk to me about existential dread ;*)



https://animeshtrivedi.github.io/

#### The goal of this talk is to ...

- Tell you all the things that I find exciting *luckily that is also my job :*)
  - Without pulling hairs and splitting electrons
- Get you excited about storage systems
  - Even if you are not interested "<u>in</u>" storage systems you should know what it can offer to you for your data-driven workloads!
  - If you *are* interested, just chat up with me after this talk
- Convince you it is not just about writing code
  - CS, AI, and Mathematics we need help from all of you!
- Lastly, right now it is very fun and exciting time to do advanced studies
   The field of computing is undergoing a fundamental shift *you can shape it*

## When I say Storage Systems...



Storage System Course, <u>https://animeshtrivedi.github.io/course-stosys/</u> https://studiegids.vu.nl/en/2021-2022/courses/XM\_0092#/

#### Data, Data, and Data Everywhere



#### A minute on the Internet





https://new.in-24.com/News/120299.html

https://cybersecurityventures.com/the-world-will-store-200-zettabytes-of-data-by-2025/

Assume:

• 1 grain of rice is 1 byte of data



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- Kilobyte: a cup of rice



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#### "Find me an image of a pink cat"





# How do we store and process this data?

|                                      |              | Cheetah 15K.5 |  |
|--------------------------------------|--------------|---------------|--|
|                                      | Capacity     | 300 GB        |  |
|                                      | RPM          | 15,000        |  |
|                                      | Average Seek | 4 ms          |  |
| Invented by IBM in <u>1956</u>       | Max Transfer | 125 MB/s      |  |
| -                                    | Platters     | 4             |  |
| The primary technology to store data | Cache        | 16 MB         |  |
| The primary technology to store data | Connects via | SCSI          |  |
|                                      |              |               |  |

Lots of work and research has been done on it to ...

- **Store data** in a single machine
- Store data **reliably** in a single machine
- Store data reliably with **high-performance** in a single machine
- Store data on distributed machines
- Store data **reliably** on distributed machines
- Store data reliably with high-performance on distributed machines

read-write

arm assembly

HDD

Platters

Spindle

R/W Head Actuator Arm

Actuator Axis Actuator

sector s

cylinder  $c \rightarrow$ 

#### HDD Design Mantras - Since the 1960s

- 1. I/O read/write operations happens in a sector granularity (512 bytes)
- 2. Read and write are <u>symmetric</u> they both have the same performance
- 3. Random performance (both read/write) are worse than the sequential performance
- 4. Small I/O performance is bad cannot amortize the seek and rotational time
- 5. [Not so well known] Outer vs inner track performance
  - a. Outer tracks rotate with a faster linear speed than Inner tracks
  - b. Hence, faster bandwidth (30+%) and lower latencies
  - c. See section 4.3 <u>http://cseweb.ucsd.edu/~gmporter/papers/tritonsort-nsdi11.pdf</u>
- 6. (Theoretically) Infinite durability magnetic field can be held indefinitely
  - a. Disregarding heating, damages, demagnetization, etc.



#### Minute:

#### Latencies in perspective

| Branch mispredict  | 5 s  | Yawn            |
|--------------------|------|-----------------|
| L2 cache reference | 7 s  | Long yawn       |
| Mutex lock/unlock  | 25 s | Making a coffee |
|                    |      |                 |

#### Numbers every programmer should know

While the other components improved significantly since the 1960s ...

#### Storage has been the Achilles' heel

Incredible amount of work done to hide these latencies

#### https://gist.github.com/hellerbarde/2843375

| Main memory reference<br>Compress 1K bytes with Zippy   | 100 s<br>50 min                               | Brushing your teeth<br>One episode of a TV show (including ad breaks)                                |
|---|---|--|
| Day:  |   |  |
| Send 2K bytes over 1 Gbps network   | 5.5 hr  | From lunch to end of work day  |
| Week  |   |  |
| SSD random read<br>Read 1 MB sequentially from memory<br>Round trip within same datacenter<br>Read 1 MB sequentially from SSD | 1.7 days<br>2.9 days<br>5.8 days<br>11.6 days | A normal weekend<br>A long weekend<br>A medium vacation<br>Waiting for almost 2 weeks for a delivery |
| Year  |   |  |
| Disk seek<br>Read 1 MB sequentially from disk<br>The above 2 together   | 16.5 weeks<br>7.8 months<br>1 year            | A semester in university<br>Almost producing a new human being                                       |
|   |   |  |

#### Decade

#### Enter: USB Drive (what is inside a USB drive)



# Non-Volatile Memory (NVM) Technology

Umbrella term for many related technologies (Solid-State Storage, Storage-Class Memory - *we are rubbish with names :P*)

Overall the idea is to use physical properties of media store bits and data

- Magnetic state
- Electrical charge ←
- Crystalline / amorphous state
- Resistance
- Optical





## Flash Memory

Invented by Toshiba

- Since mid-1980s commercially available
- The basic idea of a floating gate: 1960s with the MOSFET technology

Has been around for more than 30 years

First became popular in with embedded devices

In the mainstream computing from the mid-2000s

One of the most popular technologies to store data today

A very <u>fundamental shift</u> how to store and manage data





### How does it work?



Trapping electrons in the floating gates to either let the current through or not

- You cannot overwrite (you cannot trap more electrons in trapped electrons)
- A FG must be re-programmed / erase (P/E) continuously, leading to an erosion of the the isolated oxide layer **finite P/E life cycle**
- Multiple reads over the time can also erode the charge : **read disturbance**

#### Making flash pages and blocks from flash cells



A bunch of flash cells are packed in a **page** : typically 4kB

• Typically, a unit of I/O - the page (similar to a sector size in HDD)

A bunch of flash pages packed together as a **block**: typically 64-128-256 pages (hence, a few Megabytes)

- Typically, a unit of erase (bulk erasure)
- **Recall**: you need to erase before you can write on a flash cell

Lots of parallelism available inside the device - we should use it :)

#### Write - Erase Operation in Detail



the content of page1 and page2 are lost, hence, if you want to save them then you have to copy out the whole block

# **Typical Values of Operations**

|     | Read ( <i>usec</i> ) | Write ( <i>usec</i> ) | Erase ( <mark>usec</mark> ) | P/E cycles |
|-----|----------------------|-----------------------|-----------------------------|------------|
| SLC | 25                   | 200-300               | 1,500-2,000                 | ~100,000   |
| MLC | 50                   | ~600-900              | ~3,000                      | ~10,000    |
| TLC | 75                   | ~900-1,350            | ~4,500                      | ~5,000     |

Performance might depend on:

- The technical generation of the device
- What cell technology it is using SLC, MLC or TLC
- How much data you have written to it (?, yes you read it right)
- How old the file system is
- and a few more parameters...

#### So far: Flash vs HDD (at the <u>cell level</u>)

- 1. *No moving parts* inside a flash storage
- 2. Flash read latencies are much lower than HDDs (10s of msecs vs 10s of usecs)
- 3. Asymmetric read and write performances, 10 (r) vs 100 (w) useconds
  - a. HDD have the same
- 4. *No overwriting (in-place update)* the same page again (HDD can)
- 5. [new operation] Erase operation, must erase a whole block before writing
- 6. [*new activity*] If there are valid data pages, must copy data before erase
- 7. *Finite number of times* one can erase and program flash cells
  - a. Nonetheless, like with any electron based storage, they leak and data will be eventually lost
  - b. HDDs have (theoretically) infinite durability
- 8. Read performance is uniform no difference with random or sequential at the <u>cell level</u>
- 9. Large amount of parallelism (100s of requests vs 10s of requests)
- 10. Also no mechanical parts, hence, better **energy efficiency and packaging density**

# Flash Translation Layer - The Secret Sauce

Reads writes from the software (OS, application, fs)





| CTI | Address<br>Translation              | Garbage Collection | Performance,<br>Parallelism          |
|-----|-------------------------------------|--------------------|--------------------------------------|
| FIL | Wear leveling,<br>Over-provisioning | Free blocks mng.   | Dead blocks and<br>Error Corrections |

#### FTL is the secret sauce

There is **programmability** and **intelligence** in flash devices



### Optane: A new class of NVM technology

- Jointly developed by Intel and Micron
- Uses a new type of material
  - Not publicly disclosed but thought to be a resistive bulk material
- Much faster than flash, and can be packaged as byte-addressable memory
  - Latencies in 100s of nanoseconds, Bandwidths in 10s of GBytes/sec





### Optane: Memory and storage form factors

Today available in <u>storage</u> as well as <u>memory</u> form factor

- Optane DIMMs (memory/cache) : 128GB, 256GB and 512GB DIMMs
  - Do direct load/store from the CPU to persistent DRAM
  - Denser and more energy efficient than DRAM
- Optane SSDs (as storage /dev/optane)
  - Make a file system, and do file I/O, mmap, read, and write

What does rebooting mean?





# The (new) triangle of storage hierarchy



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# ACM Turing Award 2017

#### John Hennessy and David Patterson Deliver Turing Lecture at ISCA 2018

2017 ACM A.M. Turing Award recipients John Hennessy and David Patterson delivered the Turing Lecture on June 4 at ISCA 2018 c<sup>2</sup> in Los Angeles. The lecture took place from 5 to 6 p.m. PDT and was open to the public. A video of the lecture can be viewed below.

Titled "A New Golden Age for Computer Architecture: Domain-Specific Hardware/Software Co-Design, Enhanced Security, Open Instruction Sets, and Agile Chip Development," the talk covers recent developments and future directions in computer architecture.

Hennessy and Patterson were recognized with the Turing Award for "pioneering a systematic, quantitative approach to the design and evaluation of computer architectures with enduring impact on the microprocessor industry."





#### CONTRIBUTED ARTICLES

#### A New Golden Age for Computer Architecture



#### Watch and read them all ;) (really you should)



#### **TURING LECTURES**

Presented by each winner on the topic of their choice at a forum of their choice in the year they received the ACM A.M. Turing Award.

(2018) Hinton, Geoffrey E
The Deep Learning Revolution
LeCun, Yann

The Deep Learning Revolution: The Sequel

(2017) Hennessy, John L

A New Golden Age for Computer Architecture
 Patterson, David
 A New Golden Age for Computer Architecture

(2016)

Berners-Lee, Tim

🙍 💶 The World Wide Web

#### (1991)

Milner, Arthur John Robin Gorell ("Robin")

#### (1990)

Corbato, Fernando J ("Corby") On building systems that will fail

(1988)

Sutherland, Ivan Micropipelines

(1987) Cocke, John The search for performance in scientific processors



#### CHRONOLOGICAL LISTING OF A.M. TURING AWARD WINNERS

\* person is deceased

(2019)Catmull, Edwin E. Hanrahan, Patrick M. (2018)Bengio, Yoshua Hinton, Geoffrey E LeCun, Yann (2017)Hennessy, John L Patterson, David (2016)Berners-Lee, Tim (2015)Diffie, Whitfield Hellman, Martin (2014)Stonebraker, Michael Lamport, Leslie

(2000) Yao, Andrew Chi-Chih (1999)

Brooks, Frederick ("Fred") (1998) Gray, James ("Jim") Nicholas \*

(1997) Engelbart, Douglas \*

(1996) Pnueli, Amir \*

(1995) Blum, Manuel

(1994) Feigenbaum, Edward A ("Ed") Reddy, Dabbala Rajagopal ("Raj")

(1993) Hartmanis, Juris Stearns, Richard ("Dick") Edwin (1981) Codd, Edgar F. ("Ted") \*

(1980)

Hoare, C. Antony ("Tony") R.

(1979) Iverson, Kenneth E. ("Ken") \*

(1978) Floyd, Robert (Bob) W \*

(1977) Backus, John \*

(1976) Rabin, Michael O. Scott, Dana Stewart

(1975) Newell, Allen \* Simon, Herbert ("Herb") Alexander \*

(1974) Knuth, Donald ("Don") Ervin

# **CPU Performance Stalling**

Figure 6. Growth of computer performance using integer programs (SPECintCPU).



- Stalled frequency scaling
- Stalled **core** scaling
- Limited TDP
- CMOS scaling (7- nm)
- Memory wall

# **The Bigger Context**









- The compute accelerators are mainstream : GPUs, FPGA, DSAs
  - 100x performance improvements
- Network is improving we have 200 Gigabits/s links now, and Terabit/s in works
  - Expected 10-100x performance improvements
- **NVM storage is improving** 10+ Gigabytes/s with single digit microsecond latencies
  - Expected 10-100x performance improvements
- The CPU performance is stalled

**Example:** The work that the CPU was doing for HDD (in ~msecs)

(a) Now must be done in ~usec! ⇒ Efficiency (new implementations and data structures)

(b) Cannot be done at all ⇒ Specialization : for computation, for network, and for storage!

# **1/3:** Implications for AI/ML



**How much DRAM?** The training for a 40.8 MBytes of a 1001-layer ResNet model can take up to 67.2 GBytes (1000x). How much memory do you need for 1 Trillion parameter model? I am sure many times you run out of memory even for current models on the GPU?

Parameter counts in Machine Learning, https://www.lesswrong.com/posts/GzoWcYibWYwlva8aL/parameter-counts-in-machine-learning Using DeepSpeed and Megatron to Train Megatron-Turing NLG 530B, the World's Largest and Most Powerful Generative Language Model, https://www.microsoft.com/en-us/research/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-gene rative-language-model/ Turing-NLG: A 17-billion-parameter language model by Microsoft, https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/

#### AI Can Do Great Things—if It Doesn't Burn the Planet

The computing power required for AI landmarks, such as recognizing images and defeating humans at Go, increased 300,000-fold from 2012 to 2018.



LAST MONTH, RESEARCHERS at <u>OpenAI</u> in San Francisco revealed an algorithm capable of learning, through trial and error, how to <u>manipulate the pieces of a Rubik's Cube</u> using a robotic hand. It was a remarkable research feat, but it required more than 1,000 desktop computers plus a dozen machines running specialized graphics chips crunching intensive calculations for several months.

The effort may have consumed about 2.8 gigawatt-hours of electricity, estimates Evan Sparks, CEO of <u>Determined AI</u>, a startup that provides software to help companies manage AI projects. That's roughly equal to the output of three nuclear power plants for an hour. A

This is not to say that AI/ML is bad, but to point out that we have an opportunity to **smartly design storage and memory systems** to deliver efficiency

- Scale
- Cost
- Energy and Sustainability

# 2/3: Implications for Data Structures

#### FIGURE 9: THE RUM CONJECTURE read (read optimized) point: indexes adaptive differential DS update update (vrite optimized) (space optimized)

# **The RUM Conjecture:** Need for efficient data-structure designs

# Read-heavy, write-heavy, mixed, range scans, concurrency, batch operations

• Modeling, statistics, and analysis

Algorithms Behind Modern Storage Systems, <a href="https://queue.acm.org/detail.cfm?id=3220266">https://link.springer.com/article/10.1007/s00778-019-00559-8</a> Indexing in flash storage devices: a survey on challenges, current approaches, and future trends, <a href="https://link.springer.com/article/10.1007/s00778-019-00559-8">https://link.springer.com/article/10.1007/s00778-019-00559-8</a>

| Index                                 | Search   | Insertion   | Space        | Experimental evaluation               |
|---------------------------------------|--|---|--------------|---------------------------------------|
| SCATTERED LOGGING                     |  |   |              |                                       |
| BFTL [ <u>149</u> , <u>151</u> ]      | h * c  | $\begin{array}{l} 2(\frac{1}{M-1}+\tilde{N}_{\rm split} \\ +\tilde{N}_{\rm merge/rotate}) \end{array}$  | n * c + B    | B-tree                                |
| WOBF [51]                             | -  | -   | -            | BFTL, IBSF                            |
| SCATTERED LOGGING & NODE              | MODIFICATION   |   |              |                                       |
| FlashB-tree [73]                      | (h, h * c)   | $\frac{1}{n_{in}}(\frac{2}{3} * \tilde{N}_{split})$   | n + B        | BFTL, IBSF                            |
| NODE MODIFICATION                     |  |   |              |                                       |
| uB+tree [141]                         | -  | -   |              | B+tree                                |
| BF-tree [7]                           | $egin{array}{l} h+[p_{ m fp}\ st n_{pl}]_{sr} \end{array}$ | -   | $n * n_{pl}$ | B+tree, FD-tree, hashing              |
| IN MEMORY BUFFERING                   |  |   |              |                                       |
| IBSF [88]                             | h  | $\frac{1}{n_{\rm in}}(\tilde{N}_{\rm split} + \tilde{N}_{\rm merge/rotate})$  | n + B        | BFTL                                  |
| RBFTL [152]                           | -  | -   | -            | B-tree                                |
| LU B+tree [ <u>116</u> ]              | -  | -   | -            | B+tree                                |
| TNC [59]                              | -  | -   | -            | -                                     |
| AS B-tree [123]                       | -  | -   | -            | B+tree, BFTL, LA-tree                 |
| FLASH BUFFERING                       |  |   |              |                                       |
| FD-tree [ <u>98</u> , <u>99</u> ]     | $\log_k n$   | $[\frac{k}{f-k}\log_k n]_{srw}$   | c * n        | B+tree, BFTL, LSM-tree                |
| FD+tree, FD+FC [139]                  | $\log_{\gamma} \frac{n}{\kappa_0 \beta}$                   | $\left[\frac{\gamma}{\beta-\gamma}\log_{\gamma}\frac{n}{\kappa_{0}\beta}\right]_{srw}$  | c * n        | FD+XM, FB+DS [139]                    |
| BSMVBT [34]                           | -  | -   | -            | TMVBT [57]                            |
| FLASH BUFFERING & NODE M              | ODIFICATION  |   |              |                                       |
| AB-tree [64]                          | $\sum_{l=1}^{h} \frac{M^{d-1}}{N_l} l$                     | $h/s_n$   | n            | B+tree, BFTL, FD-tree                 |
| WPCB-tree [61]                        | h  | $egin{array}{llllllllllllllllllllllllllllllllllll$  | n+B          | B-tree, the d-IPL, $\mu*\text{-tree}$ |
| IN MEMORY BUFFERING & NO              | DE MODIFICATION  |   |              |                                       |
| MB-tree [124]                         | $\frac{2+\lceil \log_M}{\frac{2*n}{M*n_l}}\rceil$          | $ \begin{array}{c} [3/n_{\mathrm{f}}]_{\mathrm{w}} \\ + \left[ (n_{l} + \lceil \log_{M} \frac{2 \ast n}{M \ast n_{l}} \rceil) \\ /n_{\mathrm{f}} \right]_{\mathrm{r}} \end{array} $ | n+B          | BFTL, B+tree(ST), B-tree              |
| FB-tree [75]                          | -  | -   | -            | B+tree                                |
| Bw-tree [92, 93]                      | -  | -   | -            | BerkeleyDB, Skip List                 |
| Bloom tree [66]                       | $egin{array}{c} h+p_{ m fp}*d\ +2 \end{array}$             | -   | n + B        | B+tree, B+tree(ST), FD-tree, MB-tree  |
| IN MEMORY BUFFERING & IN I            | MEMORY BATCH READ  | BUFFERING & NODE MODIFICATION   |              |                                       |
| PIOB-tree [ <u>125</u> , <u>126</u> ] | $h - 1 + t_L$  | $\begin{split} & [\sum_{l=[\eta]}^{h-2} \frac{1}{G(l)} + \frac{1}{G(h-1)}]_l + [\frac{1}{G(h-1)}]_w \\ & - \frac{1/M^{r(\theta \times 1)}}{G(\log_{W}(\mu-B)-1)} \end{split}$       | $n + \mu$    | BFTL, FD-tree, B+tree                 |

### 3/3: Implications for CS/Systems - Pick Anything ;)



### What you should remember from this talk

#### 1. Data sizes are exploding

a. Bioinformatics, edge computing, social media, scientific experiments, farming ...

#### 2. Storage is no longer a bottleneck

- a. Data accesses in 10s of microseconds with millions operations /sec
- b. Can help to compliment DRAM data accesses (Optane)
- 3. The field of computing is changing *towards specialization* 
  - a. Where you store data: DRAM, Flash, Optane, HDDs, Tape
  - b. How do you store data: block, objects, files, tensors, tree, link lists, hash tables
  - c. How do you access: synchronous, interrupts, scheduling, fast/slow paths, programmability
  - d. You can ask to tailor a storage stack for you own needs performance, and cost
- 4. Efficiency of data storage cost and computation is important

### To Conclude

#### Storage Research is fundamentally changing and reshaping what **kind of systems we can build tomorrow**

- Better performance
- New specialized abstractions
- Better cost and energy efficiency
- Superior scalability
- And much more ...

#### Data Storage Research Vision 2025

Report on NSF Visioning Workshop held May 30-June 1, 2018

George Amvrosiadis<sup>†</sup>, Ali R. Butt<sup>¶</sup>, Vasily Tarasov<sup>‡</sup>, Erez Zadok<sup>\*</sup>, Ming Zhao<sup>§</sup>

Irfan Ahmad, Remzi H. Arpaci-Dusseau, Feng Chen, Yiran Chen, Yong Chen, Yue Cheng, Vijay Chidambaram, Dilma Da Silva, Angela Demke-Brown, Peter Desnoyers, Jason Flinn, Xubin He, Song Jiang, Geoff Kuenning, Min Li, Carlos Maltzahn, Ethan L. Miller, Kathryn Mohror, Raju Rangaswami, Narasimha Reddy, David Rosenthal, Ali Saman Tosun, Nisha Talagala, Peter Varman, Sudharshan Vazhkudai Avani Waldani, Xiaodong Zhang, Yiying Zhang, and Mai Zheng.

> <sup>†</sup>Carnegie Mellon University, <sup>¶</sup>Virginia Tech, <sup>‡</sup>IBM Research, <sup>\*</sup>Stony Brook University, <sup>§</sup>Arizona State University

> > February 2019

#### **Executive Summary**

With the emergence of new computing paradigms (e.g., cloud and edge computing, big data, Internet of Things (IoT), deep learning, etc.) and new storage hardware (e.g., non-volatile memory (NVM), shingled-magnetic recording (SMR) disks, and kinetic drives, etc.), a number of open challenges and research issues need to be addressed to ensure sustained storage systems efficacy and performance. The wide variety of applications demand that the fundamental design of storage systems should be revisited to support application-specific and application-defined semantics. Existing standards and abstractions need to be reevaluated; new sustainable data representations need to be designed to support emerging applications. To take advantage of hardware advancements, new storage software designs are also necessary in order to maximize overall system efficiency and performance.

Therefore, there is a urgent need for a consolidated effort to identify and establish a vision for storage systems research and comprehensive techniques that provide practical solutions to the storage issues facing the information technology community. To address this need, the National Science Foundation's (NSF) "Visioning Workshop on Data Storage Research 2025" brought together a number of storage researchers from academia, industry, national laboratories, and federal agencies to develop a collective vision for future storage research, as well as to prioritize

# The (new) triangle of storage hierarchy

