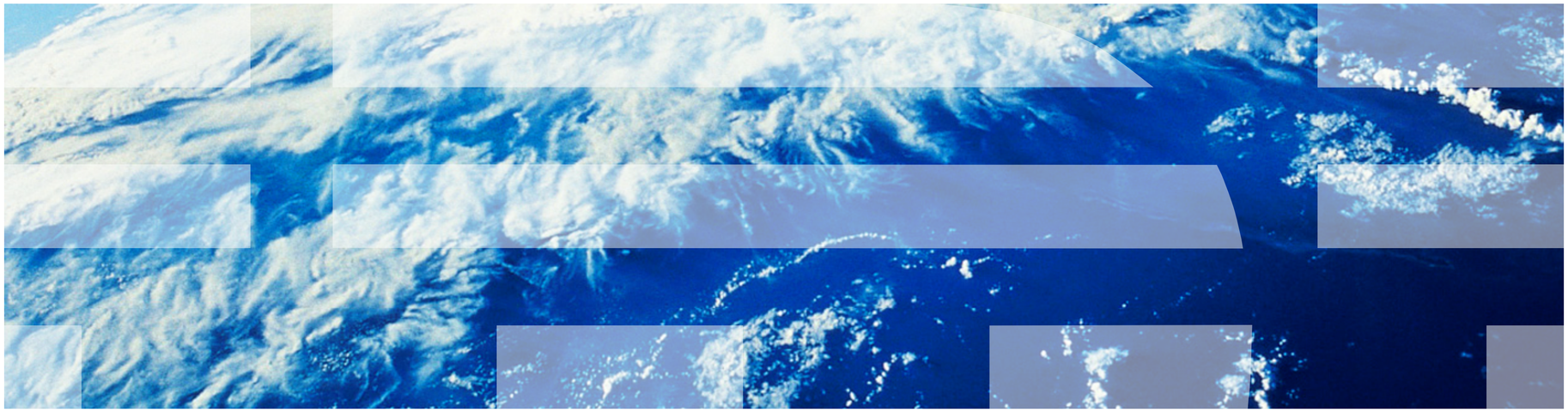
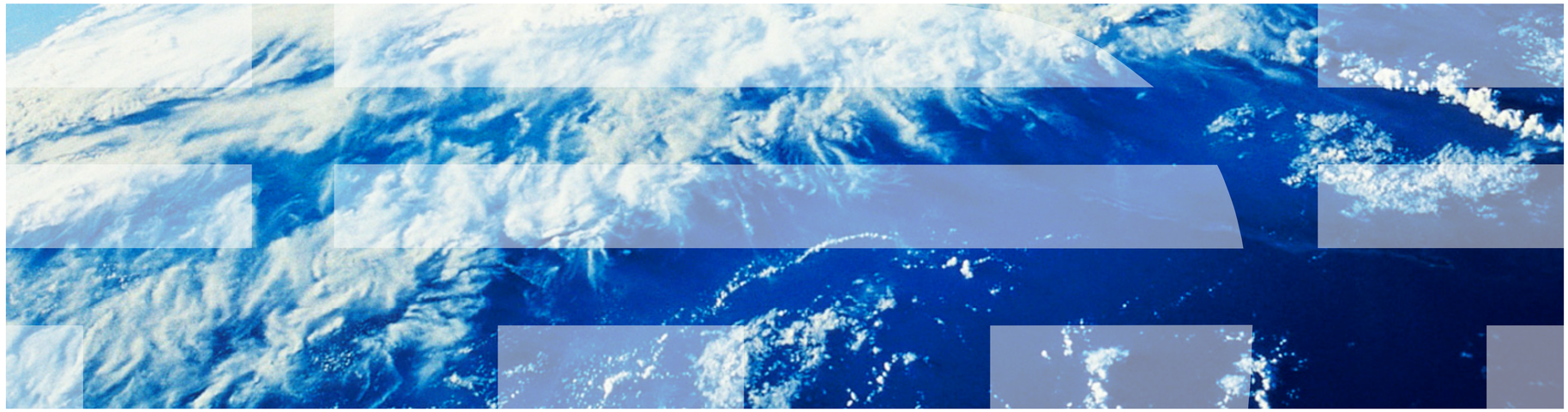
Lecture 1



Computer Systems for Data Science
Topic 1

Course Introduction

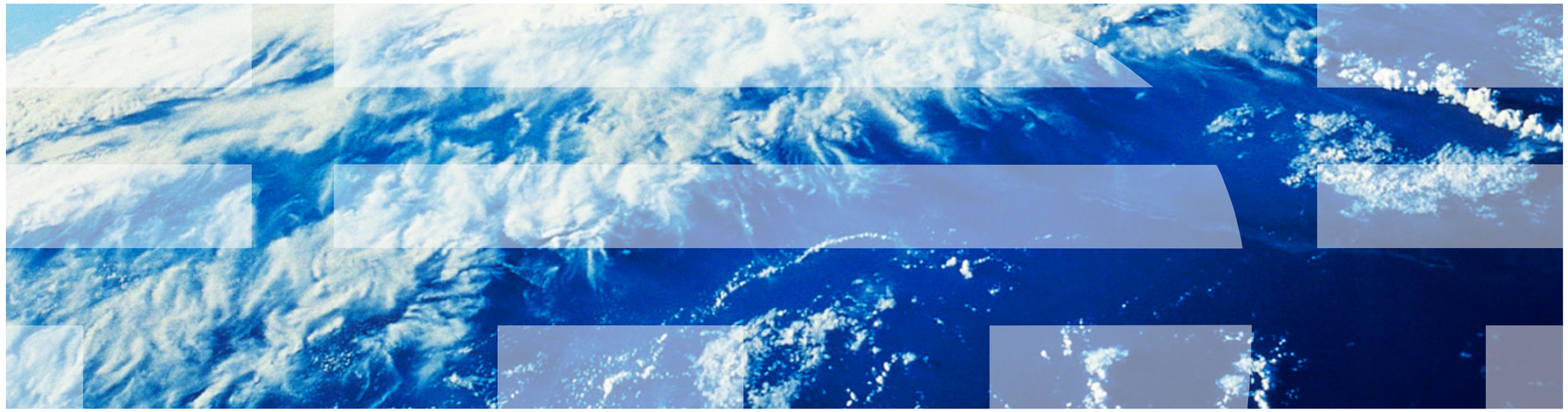
Systems concepts



Topic 1: Agenda

Intro to instructors
High-level overview
  What is data science and big data?
  Class goals and why should you care?
Class logistics
  How the class is going to work?
Performance and systems rules of thumb
Intro to datacenters

Who Are We?



Course Instructors and TAs

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- Instructor: Waqar Aqeel

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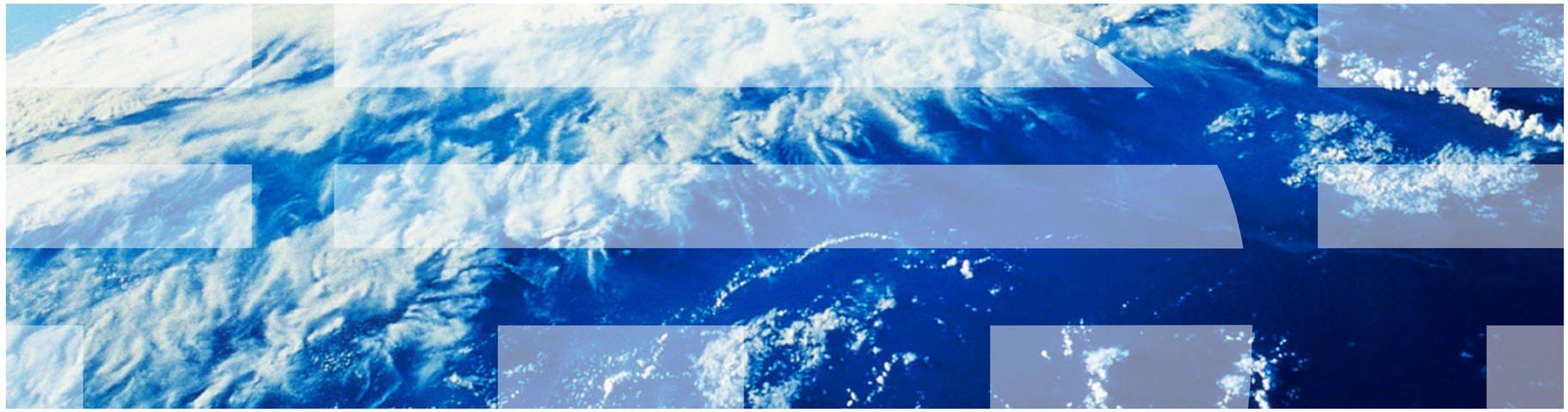
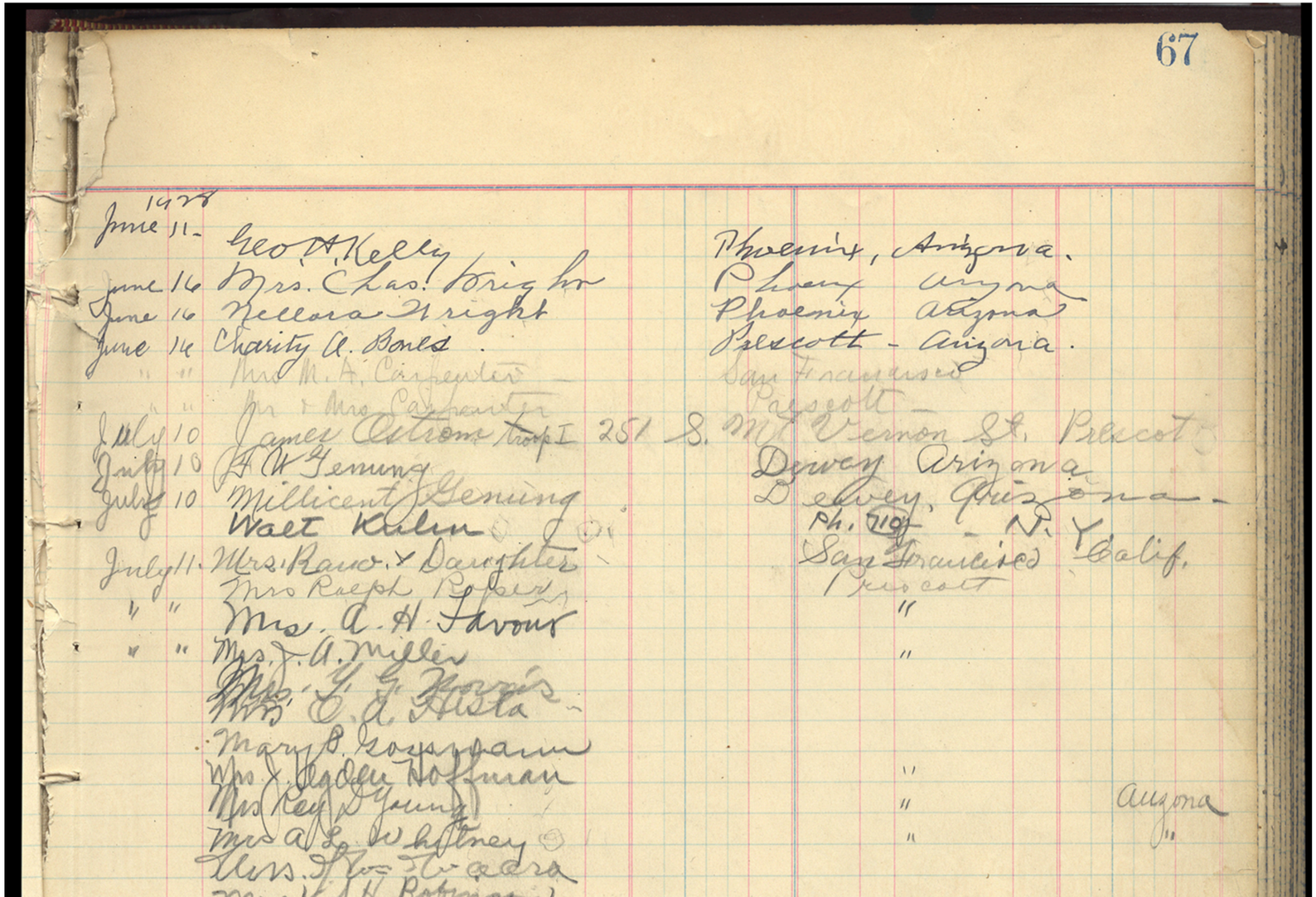
- All CAs have experience in databases and systems

What is Data Science and Big Data?



This was a system for big data



67

1928
June 11 Geo. A. Kelly — Phoenix, Arizona.
June 16 Mrs. Chas. Wright — Phoenix Arizona
June 16 Kellora Wright — Phoenix Arizona
June 16 Charity A. Bones — Prescott - Arizona.
" " Mrs M. A. Carpenter — San Francisco
" " Mr + Mrs Carpenter — Prescott
July 10 James Astrom Troop I — 251 S. Mt Vernon St. Prescot
July 10 A. H. Gemung — Dewey Arizona
July 10 Millicent L. Gemung — Dewey, Arizona
Walt Kahn — Ph. 7107 - N. Y.
July 11 Mrs. Rano + Daughter — San Francisco Calif.
Mrs Ralph Rogers — Prescott
" " Mrs. A. H. Favour — "
" " Mrs. J. A. Miller — "
Mrs. L. L. Harris
Mrs. E. A. Hasta
Mary B. Rosspaum
Mrs. Hayden Hoffman
Mrs Ray Young
Mrs A. L. Whitney — Arizona
Miss. Rose Rivera — "

Data science systems were expensive

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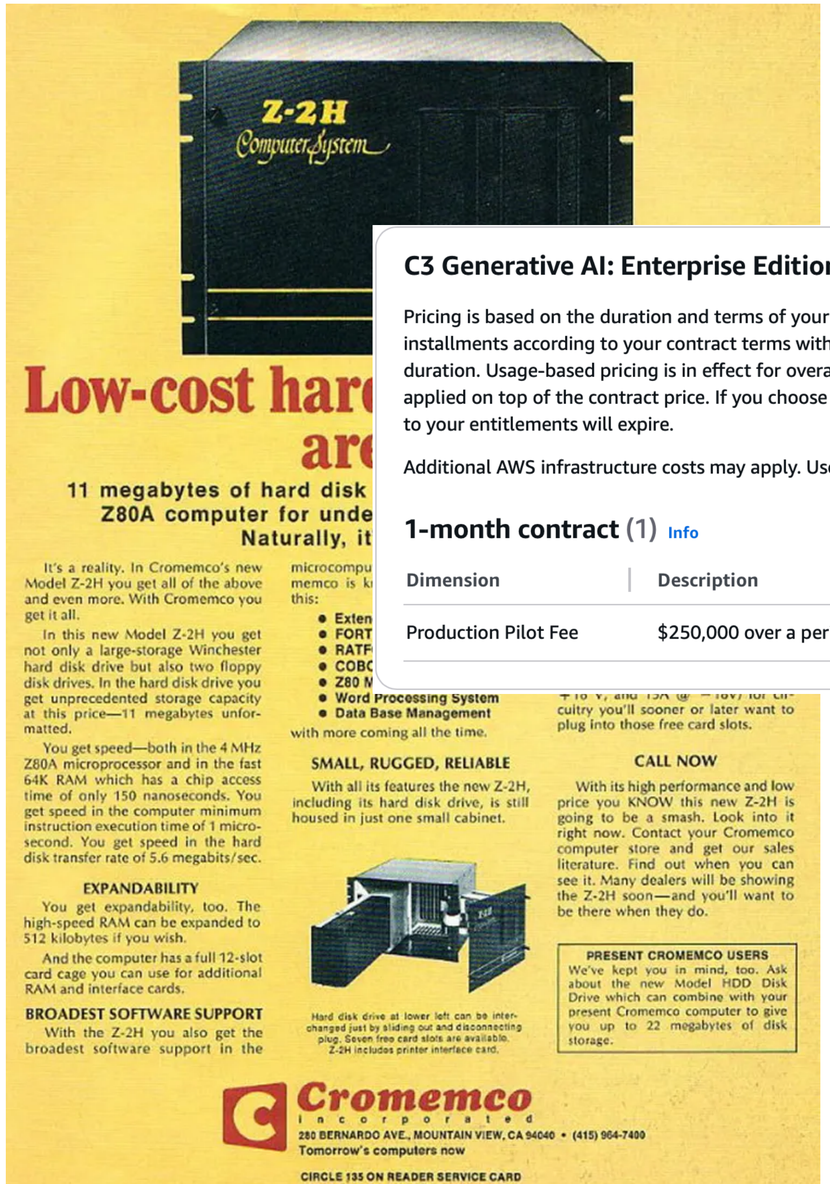


They are still expensive!

C3 Generative AI: Enterprise Edition Info

View purchase options

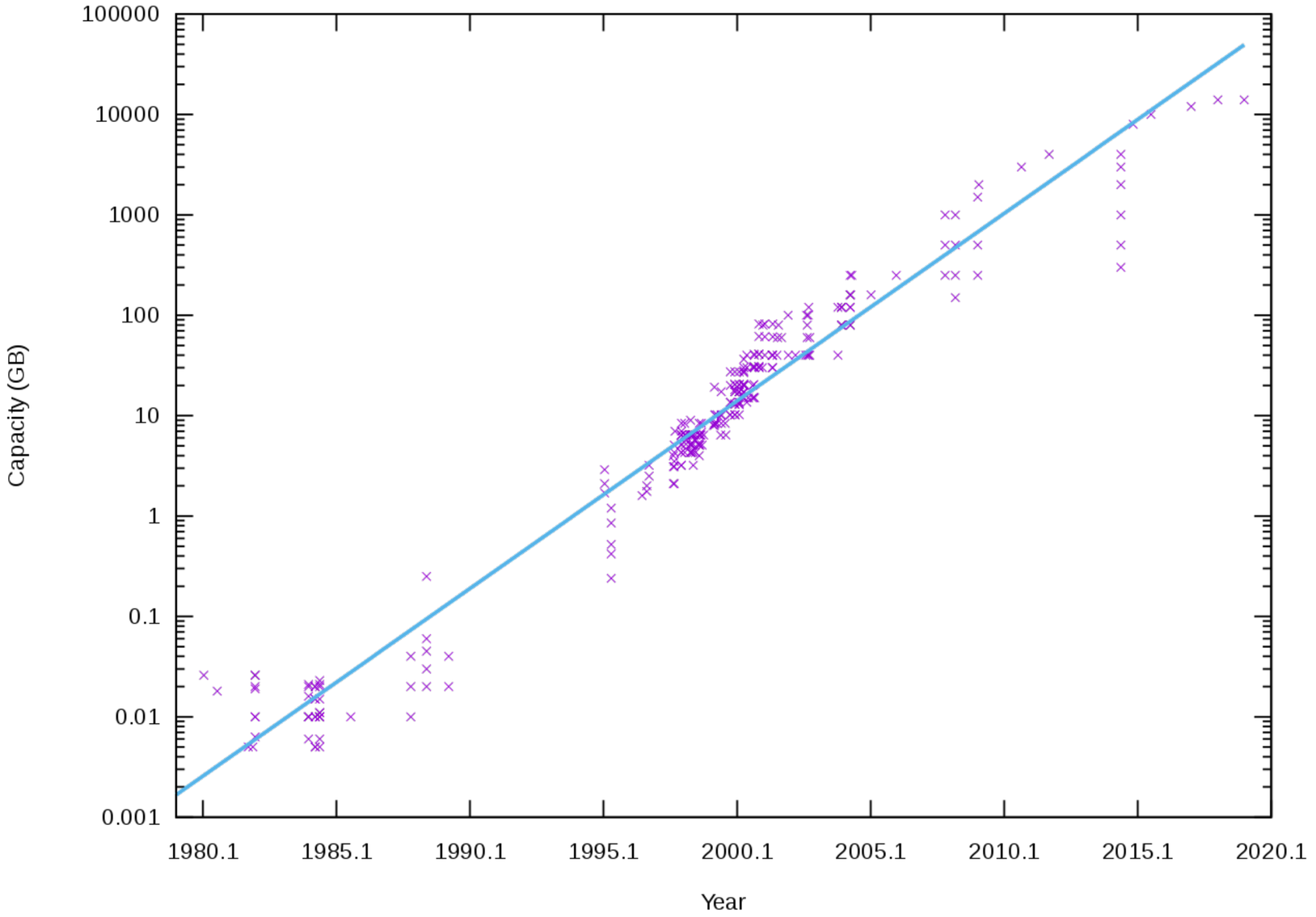
Pricing is based on the duration and terms of your contract with the vendor, and additional usage. You pay upfront or in installments according to your contract terms with the vendor. This entitles you to a specified quantity of use for the contract duration. Usage-based pricing is in effect for overages or additional usage not covered in the contract. These charges are applied on top of the contract price. If you choose not to renew or replace your contract before the contract end date, access to your entitlements will expire.

Additional AWS infrastructure costs may apply. Use the AWS Pricing Calculator to estimate your infrastructure costs.

1-month contract (1) Info

Dimension	Description	Cost/month	Overage cost
Production Pilot Fee	$250,000 over a period of 3 months - required with all options	$250,000.00	$0.55/unit

Today: data is cheap



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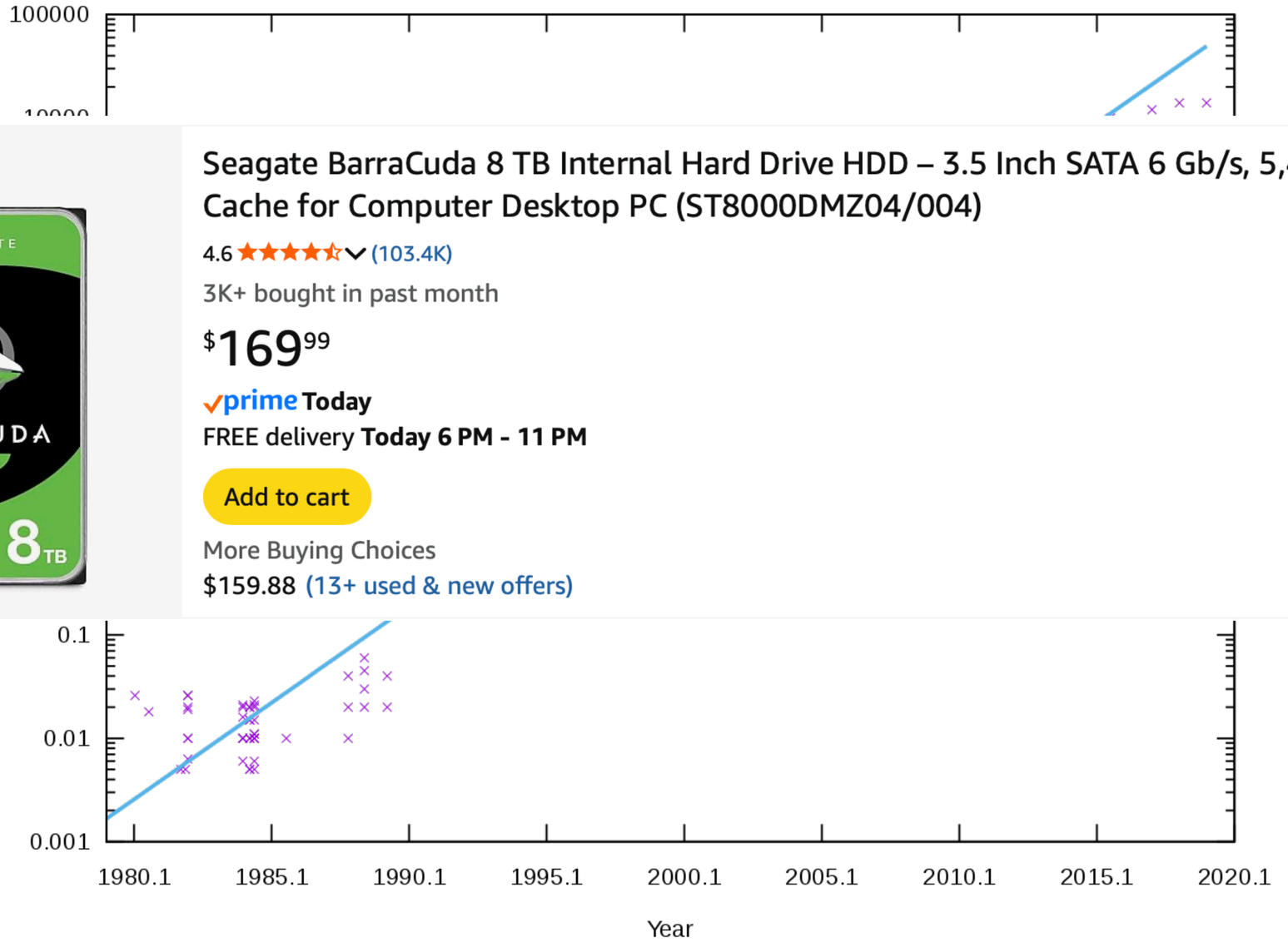

Overall Pick

Seagate BarraCuda 8 TB Internal Hard Drive HDD – 3.5 Inch SATA 6 Gb/s, 5,400 RPM, 256 MB Cache for Computer Desktop PC (ST8000DMZ04/004)

4.6 ★★★★½ (103.4K)

3K+ bought in past month

$169.99

prime Today

FREE delivery **Today 6 PM - 11 PM**

Add to cart

More Buying Choices

$159.88 (13+ used & new offers)

Where is data coming from?

- Physical devices

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- Software logs

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- Social media, website contents

What can we do with all this data?

- What video should I recommend to this user to view next?

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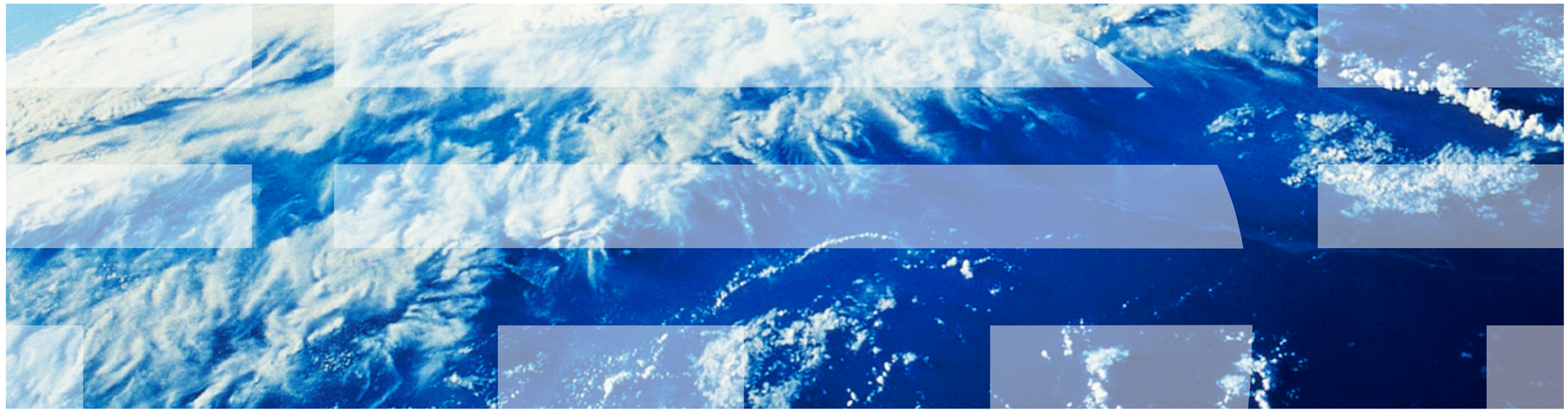
- Is the object across from the car a pedestrian?

What is big data?

- “**Extremely large data sets** that may be analyzed computationally to reveal patterns, trends, and associations, especially relating to human behavior and interactions” – Oxford Dictionary

- What’s an extremely large data set?
  - Fits on a single machine?
  - Fits on 10 machines?

What is this class about?



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  - What are the statistical/ mathematical foundations for data science?

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- **Broad overview of cloud systems that are used in data science**
  - **Database** related topics (DBMS, SQL, NoSQL, data lakes/warehouses)
  - **Computer systems** foundations (throughput vs. latency, scalability vs. performance)
  - **Distributed systems** for data scientists (sharding, fault tolerance)
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- **Required background**
  - Programming experience with Python
  - Both programming assignments will be submitted in Python

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  - No attendance required

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  - Goal: familiarize yourself with working in public cloud environment
    - AWS / Azure / GCP are similar
    - Many systems and deployment details are hidden / automated (but we won't ignore them!)
    - We will be focusing on systems-level problems, not on algorithms
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- Programming assignment goals
  - Assignment 1: BigQuery
    - Learning to use SQL on a big data set
  - Assignment 3: Indexing and filtering data structures
    - Understanding how real-world data systems data structures work, strengthen Python skills

More logistics

- **Office hours:**
  - CAs will hold office hours every weekday over Google Meet
  - Course calendar will have the meeting link: all office hours will use the same link
- **Ed**
  - A CA is guaranteed to be available on Ed every weekday (when the school is open) from 9AM – 5PM. We will try to answer your questions as fast as possible
- **Submit your assignments on time!**
  - Homework submission will be on Gradescope
  - **If you do not submit your HW on time, your grade will be 0%**
  - We will give you **plenty of time** for the assignments, don't wait until the last minute!
  - You can resubmit homework as many times as you want, until the deadline

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  - Amdahl's law
  - Back-of-the-envelope systems math
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  - JOINs
  - Nested queries
  - Transactions
  - ACID
  - OLAP vs. OLTP, SQL vs. NoSQL
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  - The memory hierarchy
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  - Mapreduce computing model
  - Stragglers
  - Lineage
  - Fault tolerance in distributed analytics: lineage
  - Streaming computing model

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  - Layered load balancing
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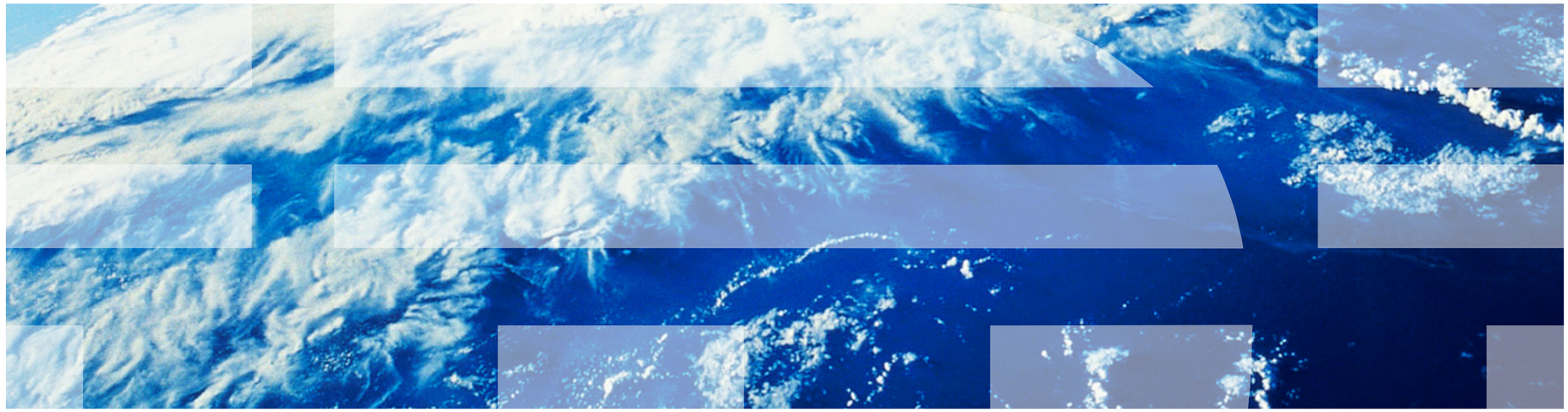
Performance Concepts and Rules of Thumb



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- Metrics allow us to compare two computer systems

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- Examples:
  - Power consumed by our database
  - CPU cost of running a web backend
  - Average time it takes to render a user page
  - How many users can we support at the same time
- Metrics allow us to compare two computer systems
- They are crucial for proving improvements, diagnosing regressions

Tradeoff: latency vs. throughput

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- Pizza delivery example
  - Do you want your pizza to be fresh?
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- A more relevant example:
  - Latency requirement: Assuming cars drive at 65mph, so self driving car needs to recognize an object in 0.1 seconds
  - Throughput requirement: Object recognition system needs to process 1 million object recognition tasks every second to support 10,000 cars simultaneously

Latency vs. Throughput is often a trade off

Plane	DC to Paris	Speed	Passengers	Throughput (pmph)
Boeing 747	6.5 hours	610 mph	470	286,700
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- Which plane has higher **performance**?
- Time to do the task (execution time)
  - **Latency**, execution time, response time
- Tasks per day, hour, week, sec (performance)
  - **Throughput**, bandwidth, operations per second
- Depends on what YOU want

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- “System X is n times faster than Y” means:
  - $n = \dfrac{performance(X)}{performance(Y)}$

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- Suppose we have a database that processes two types of queries:
  - Query A finishes in 100 seconds
  - Query B finishes in 2 seconds

- We want better performance
  - Which query should we improve?

- The answer: it depends! (a pretty lousy answer)

Speedup

- Make a change to the system
- Measure how much faster/slower it is
- $$Speedup = \frac{Execution\ time\ before\ change}{Execution\ time\ after\ change}$$

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  - $$Speedup(E) = \frac{Execution\ time\ without\ E}{Execution\ time\ with\ E} = \frac{Performance\ with\ E}{Performance\ without\ E}$$
  - $$ExTime_{new} = ExTime_{old} * \left[\left(1 - p\right) + \frac{p}{S} \right]$$
    - Explanation:
    - $\left(1 - p\right)$ is the fraction of operations that are not affected by E
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- Customers are either complaining, or they are not

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- More useful for parallel programming bottlenecks, but can be adapted here.

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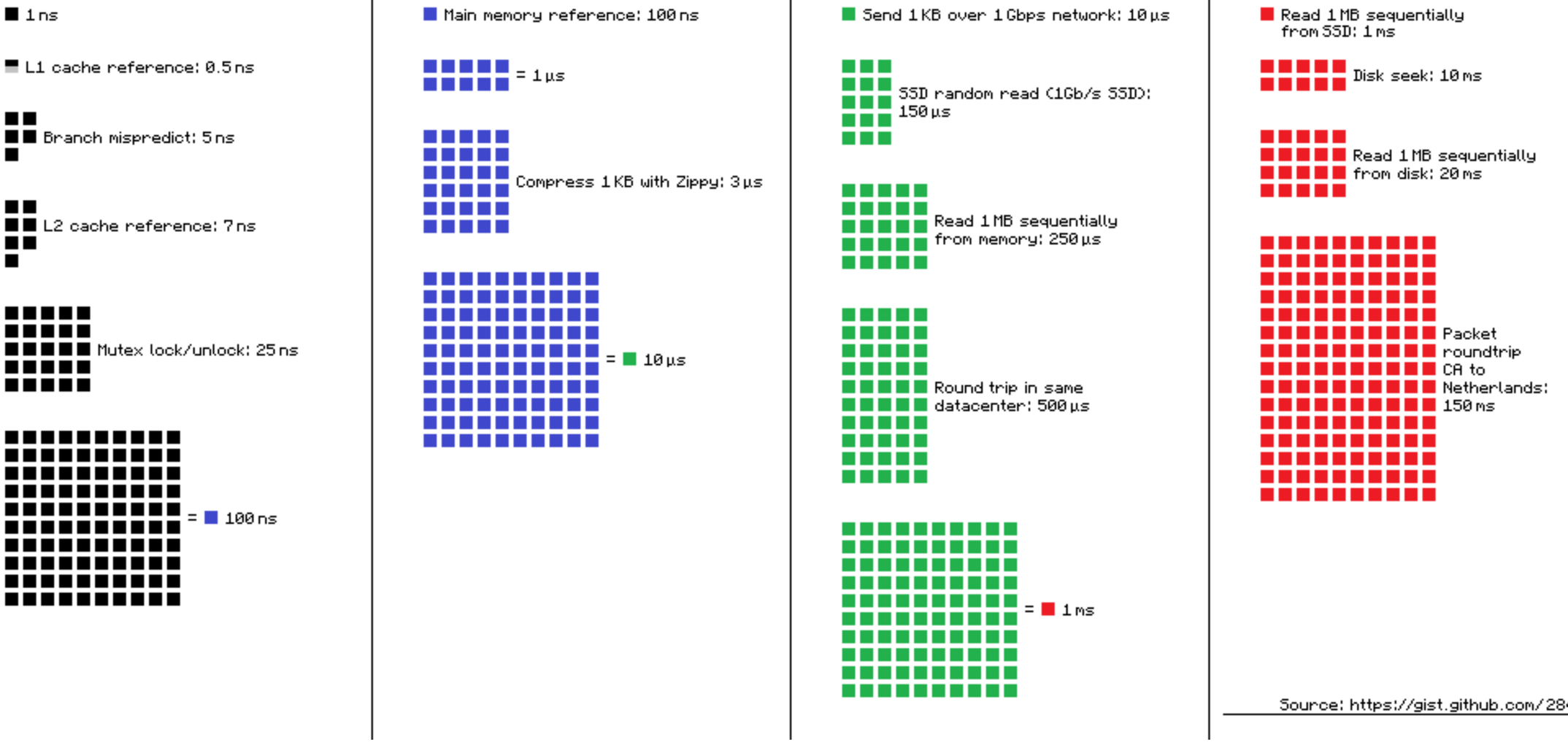
- Run a SQL query on a disk database: 20,000,000ns, 20ms
- Roundtrip time over the internet: 30,000,000us, 30ms
  - Bounded by the speed of light! Roundtrip light speed from NYC to Beijing is ~150ms

Latency Numbers Every Programmer Should Know



Source: https://gist.github.com/2841832

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- → Since 72% requests go to the database and it's so slow, its latency dominates the total latency

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- You measured: Internet roundtrip (100ms), disk DB access (10ms), flash DB access (1ms)
- Scenario 1: Your user queries involve only a single database access in the cloud (over the Internet)
  - Latency with flash database: 101ms
  - **Latency with disk database: 110ms**

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- You are considering running the database on two types of storage devices: flash vs. magnetic disk
  - You received some quotes from database company, and flash database is 2X more expensive, but 10X faster
- Your users don't notice page loading times, as long as they are under 300,000,000ns (300ms)
- You measured: Internet roundtrip (100ms), disk DB access (10ms), flash DB access (1ms)
- Scenario 1: Your user queries involve only a single database access in the cloud (over the Internet)
  - Latency with flash database: 101ms
  - **Latency with disk database: 110ms**
- Scenario 2: The app requires getting an initial response from the cloud database, then a user input, and then another cloud database request
  - Latency with flash database: 202ms
  - **Latency with disk database: 220ms**
- Scenario 3: The app requires 20 sequential databases accesses within the cloud to compute a single user query, and then it can return a response
  - **Latency with flash database: 120ms**
  - Latency with disk database: 300ms

Identifying performance bottlenecks

- My application is seeing an average latency of 200ms, where is the bottleneck?
- A few guiding questions:
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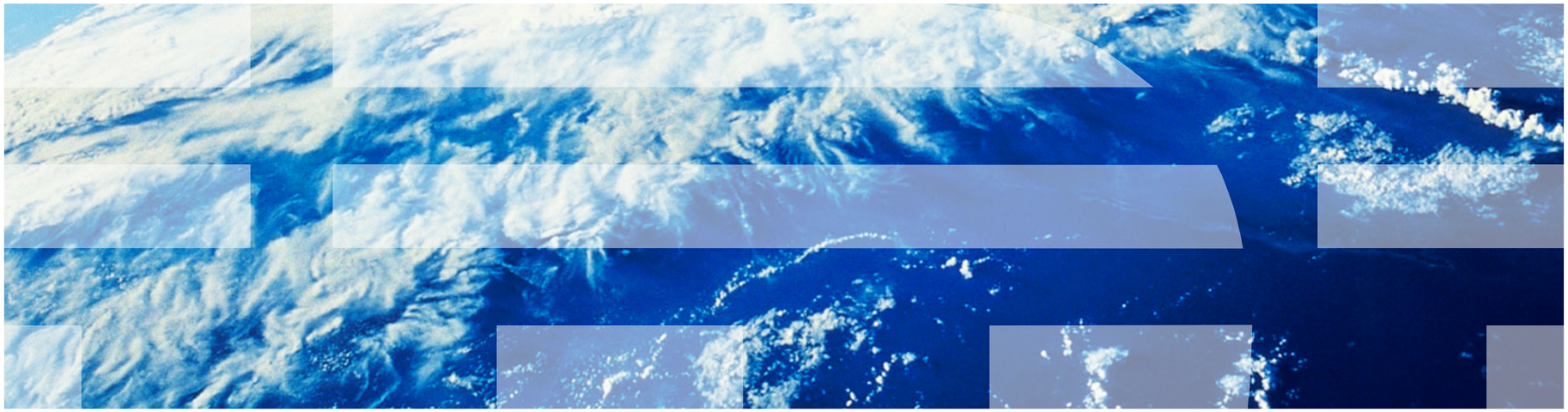
- Guess 2: database slowdown (second highest latency)

Summary

- Latency and throughput: two important metrics, sometimes correlate, but often do not
- Amdahl's law: optimize the common case
- Computer systems almost always involve a performance vs. cost trade off

Adapted from Mendel Rosenblum and Jeff Dean

The Infrastructure of Big Data



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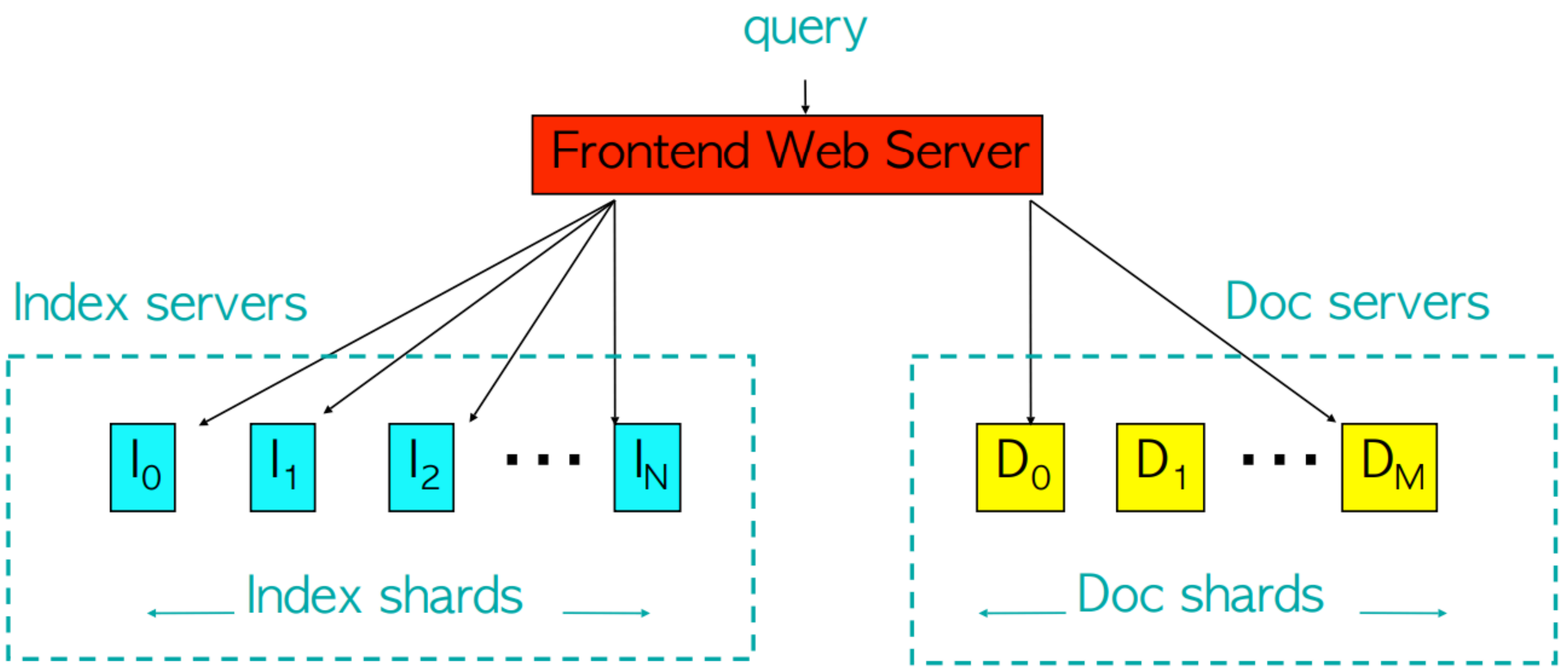
- More machines * faster machines: ~1000X

Google Circa 1997 (definitely not big data)

Google infrastructure circa 1997 could fit in a single room



Scaling up

- What happens when a server doesn’t fit in a single room?
- What happens if we need 1000X more servers?

Scaling up

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- The cloud to the rescue!
  - Also known as… **data centers**

Evolution of data centers

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- 2020’s-today:
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- Companies consider data center technology a trade-secret, especially in the age of AI
  - Limited public discussion of the state of the art from industry leaders

Power is the biggest constraint

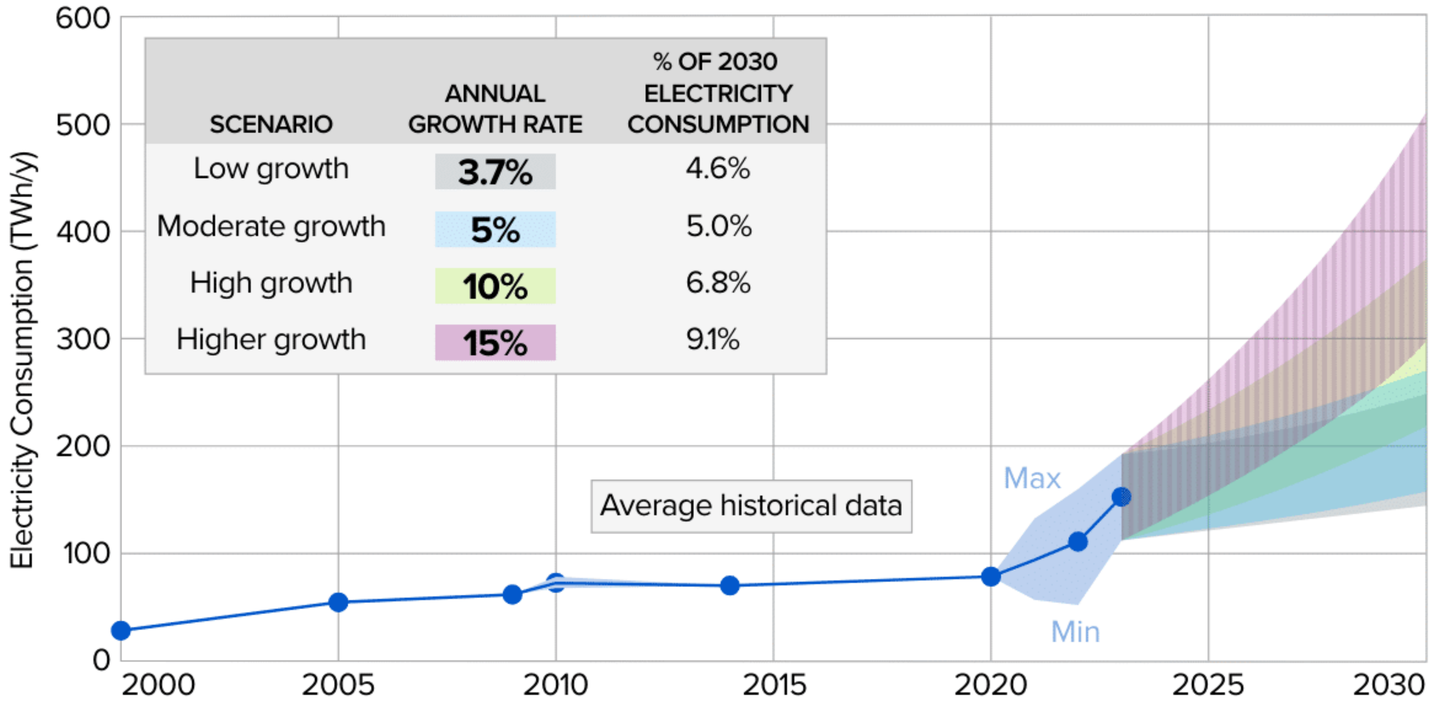


Figure ES-1. *Projections of potential electricity consumption by U.S. data centers: 2023–2030 . % of 2030 electricity consumption projections assume that all other (non-data center) load increases at 1% annually.*

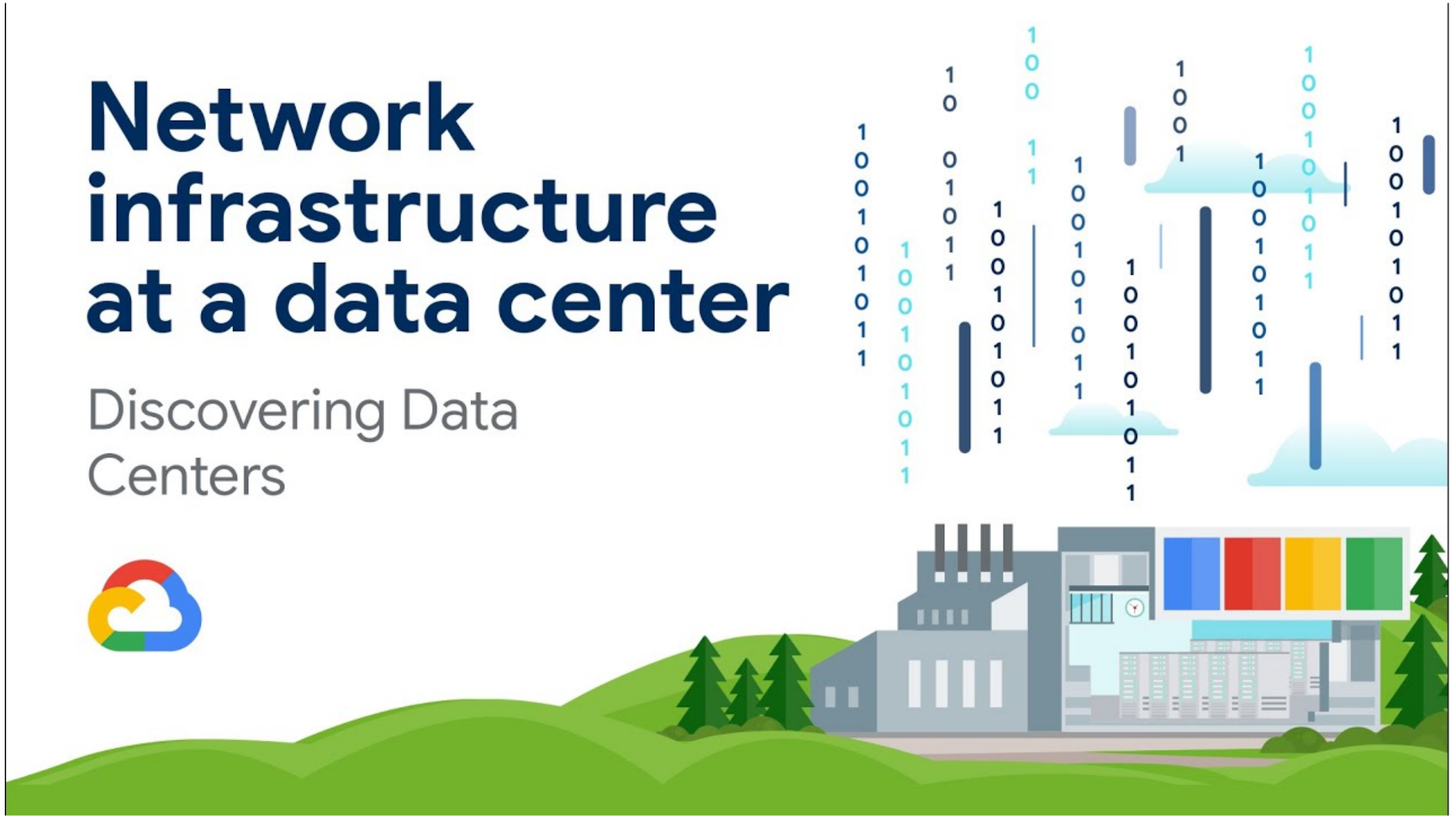
NATIONAL

Three Mile Island nuclear plant will reopen to power Microsoft data centers

Google emissions jump 48% in five years due to AI data center boom

Water and electricity use soar to record highs

Core, Edge/Satellite, PoP



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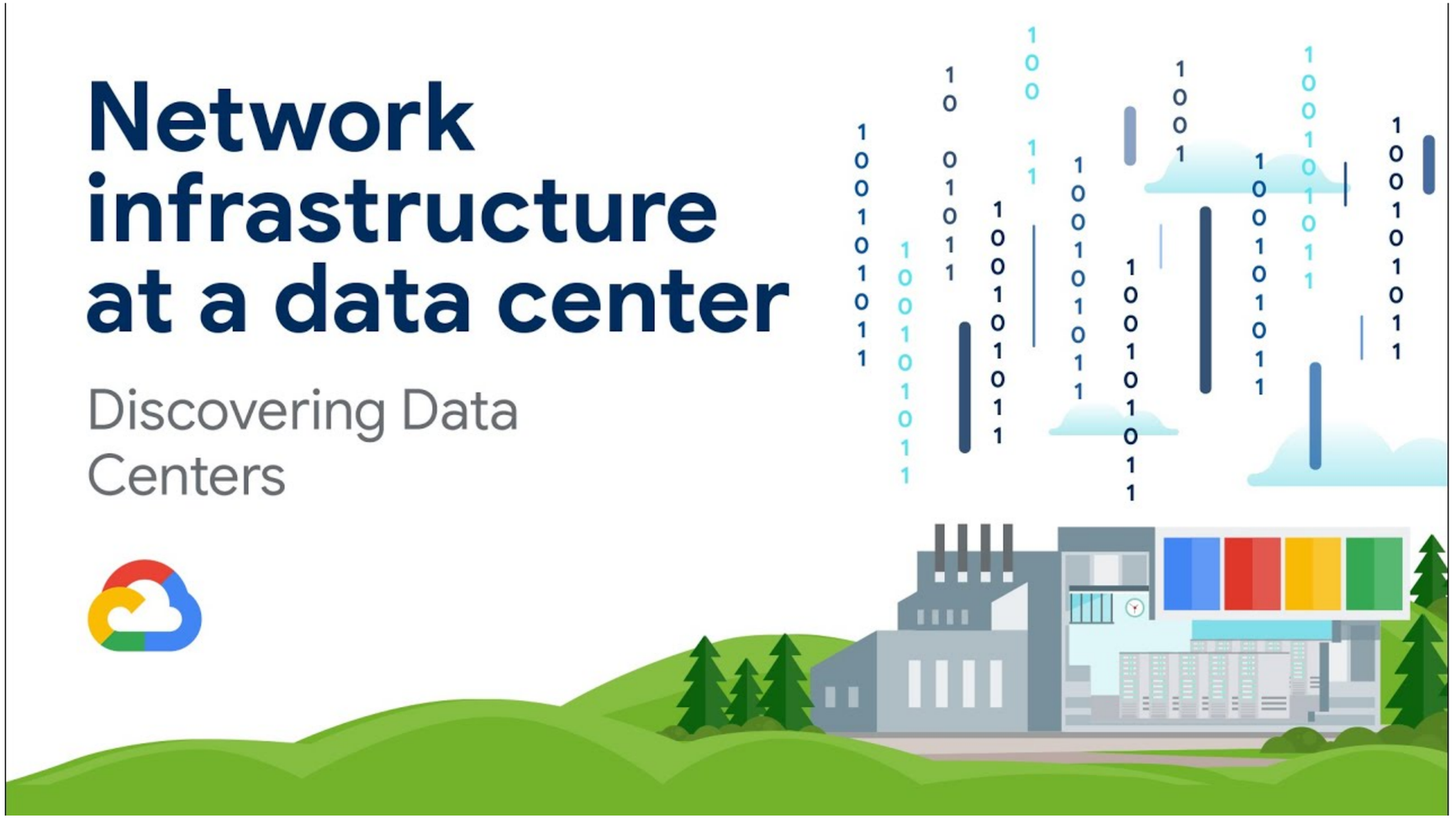
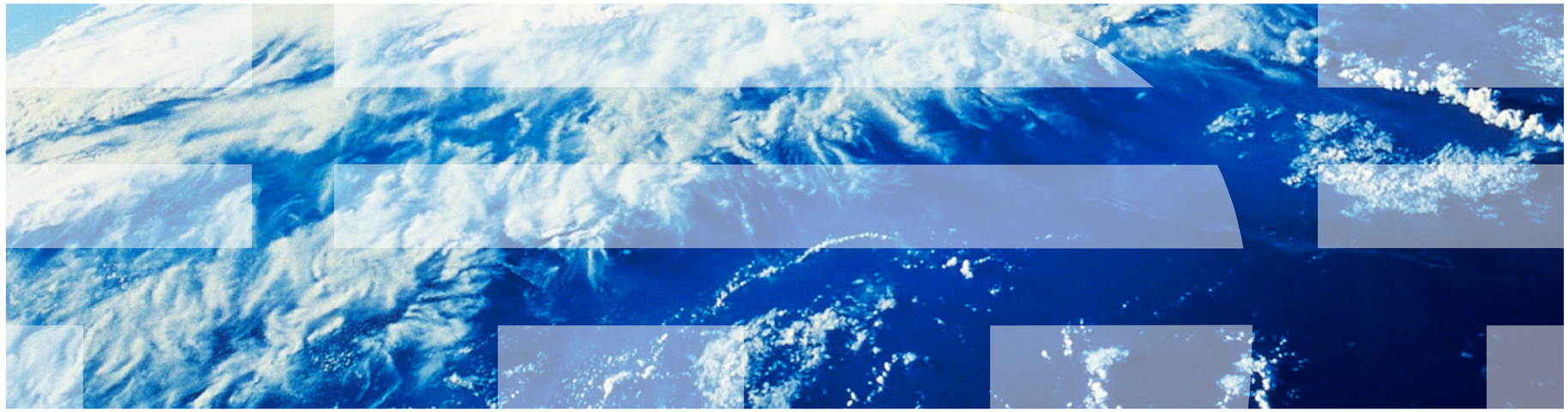


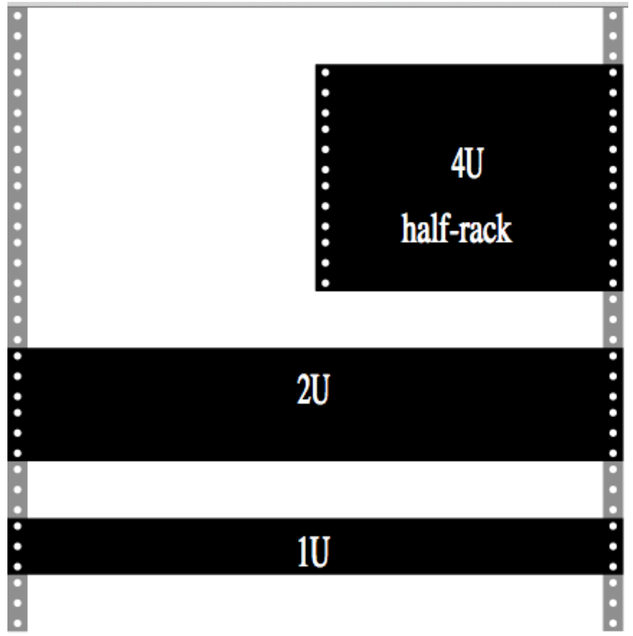
Datacenter building blocks



Rack

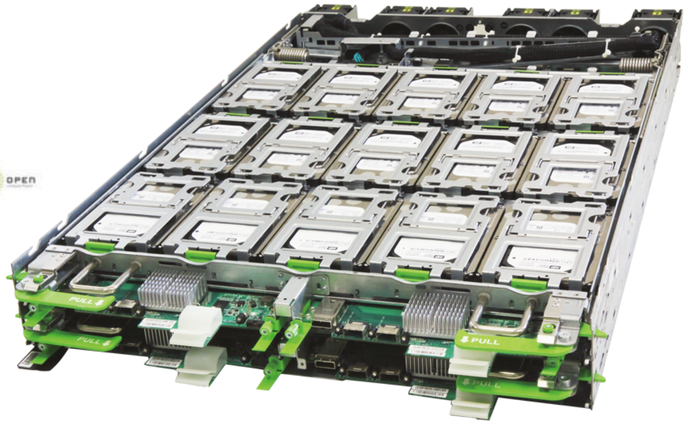
Rack

- Typically is 19 or 23 inches wide
- Typically 42 U
  - U or RU is a Rack Unit - 1.75 inches
- Slots:



Rack Slots

- Slots hold power distribution, servers, storage, networking equipment
- Typical server: 2U
  - 128-192 cores
  - DRAM: 256-512 GB
- Typical storage: 2U
  - 30 drives
- Typical Network: 1U
  - 72 100Gb/s



Project Stargate

Announcing The Stargate Project

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2 min. read · View original

The Stargate Project is a new company which intends to invest $500 billion over the next four years building new AI infrastructure for OpenAI in the United States. We will begin deploying $100 billion immediately. This infrastructure will secure American leadership in AI, create hundreds of thousands of American jobs, and generate massive economic benefit for the entire world. This project will not only support the re-industrialization of the United States but also provide a strategic capability to protect the national security of America and its allies.

The initial equity funders in Stargate are SoftBank, OpenAI, Oracle, and MGX. SoftBank and OpenAI are the lead partners for Stargate, with SoftBank having financial responsibility and OpenAI having operational responsibility. Masayoshi Son will be the chairman.