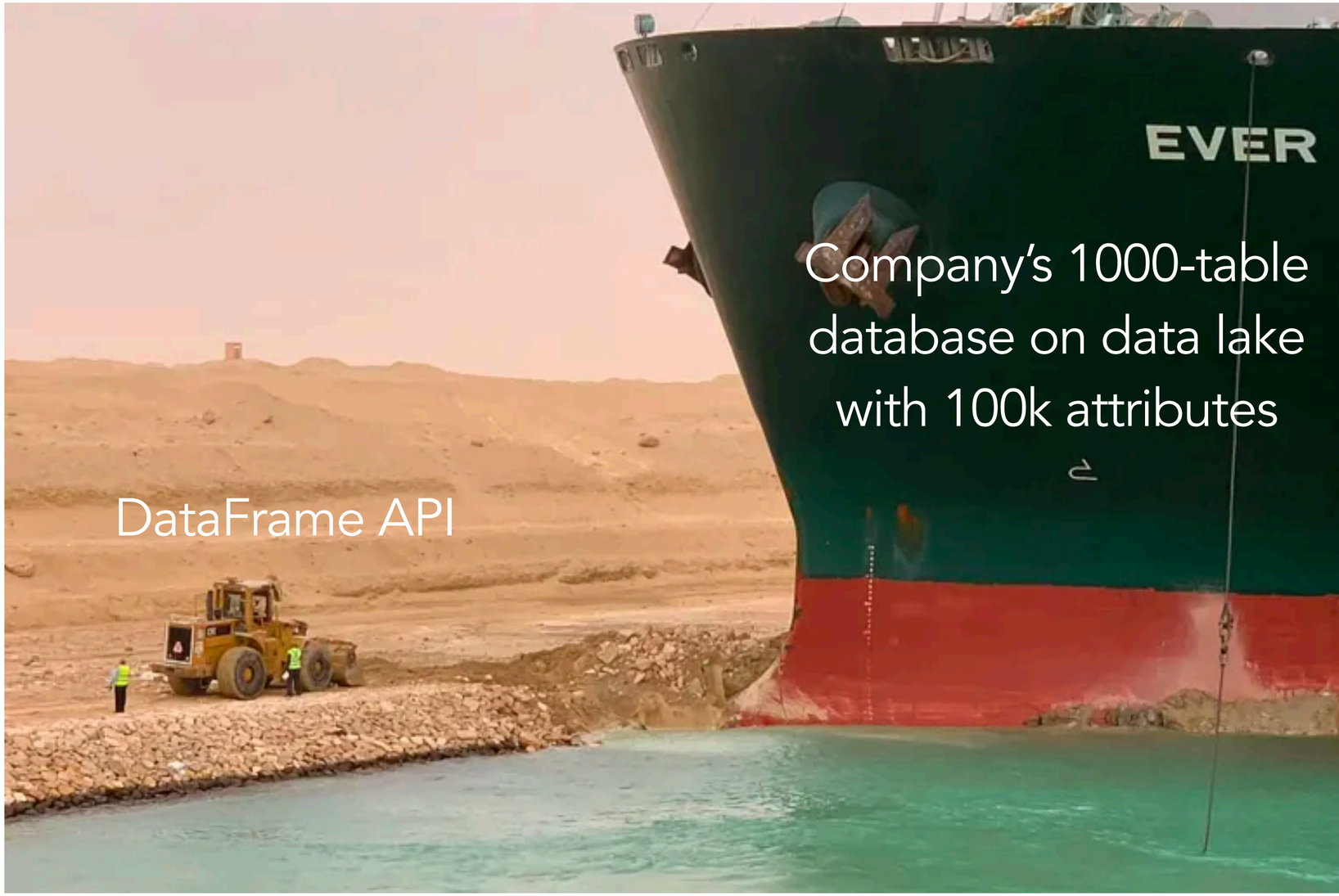
# DSC 204a Scalable Data Systems

- Haojian Jin




Meme idea credit: https://datasystemsfun.tumblr.com/

# Where are we in the class?

Foundations of Data Systems (2 weeks)

- Digital representation of Data → Computer Organization → Memory hierarchy → Process → Storage

**Scaling Distributed Systems (3 weeks)**

- Cloud → Network → Distributed storage → **Parallelism** → Partition and replication

Data Processing and Programming model (5 weeks)

- Data Models evolution → Data encoding evolution → → IO & Unix Pipes → Batch processing (MapReduce) → Stream processing (Spark)

# Today's topic: Parallelism

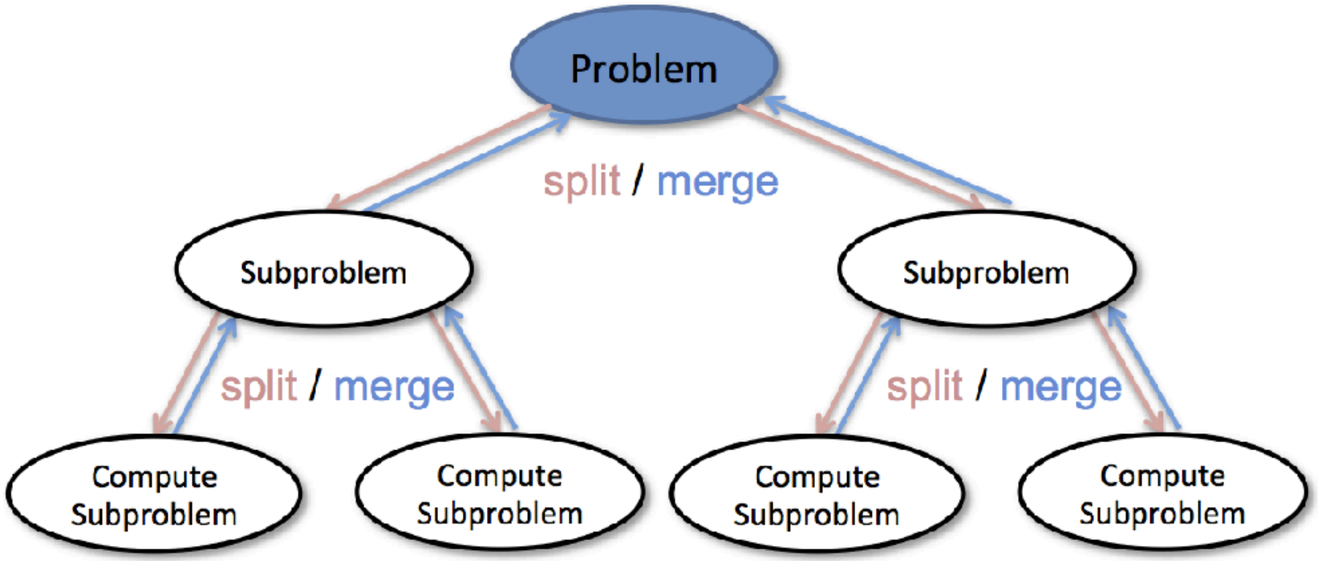
- Task parallelism & DASK
- Single-Node Multi-core; SIMD; Accelerometers

- Textbook:
  Ch. 9.4, 12.2, 14.1.1, 14.6, 22.1-22.3, 22.4.1, 22.8 of Cow Book

# Parallel Data Processing

**Central Issue**: Workload takes too long for one processor!

**Basic Idea**: Split up workload across processors and perhaps also across machines/workers (aka “Divide and Conquer”)

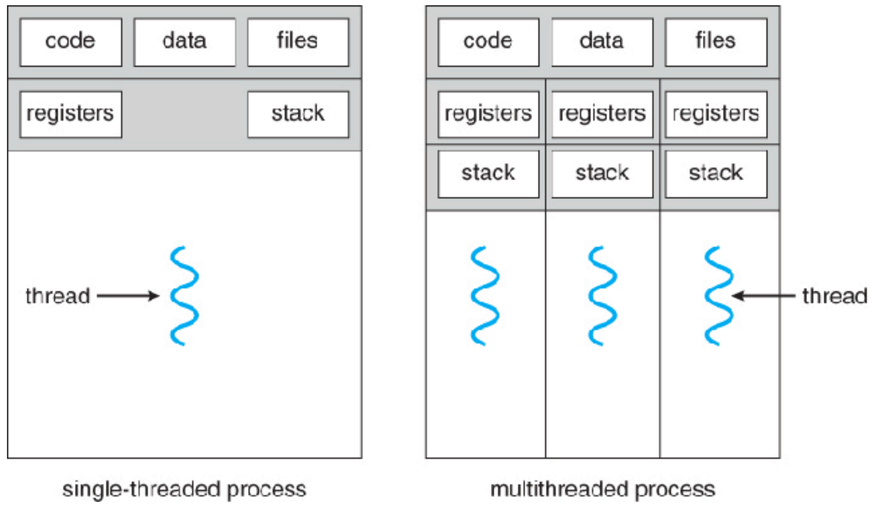





https://medium.com/cracking-the-data-science-interview/divide-and-conquer-algorithms-b135681d08fc

# New Parallelism Concept: Threads

- **Threads:** Generalization of process abstraction of OS
  - Common in parallel data processing
- A **multi-threaded** program/ process *spawns* many threads
  - Each runs its part of program's computations simultaneously
  - All threads share address space (so, data too)



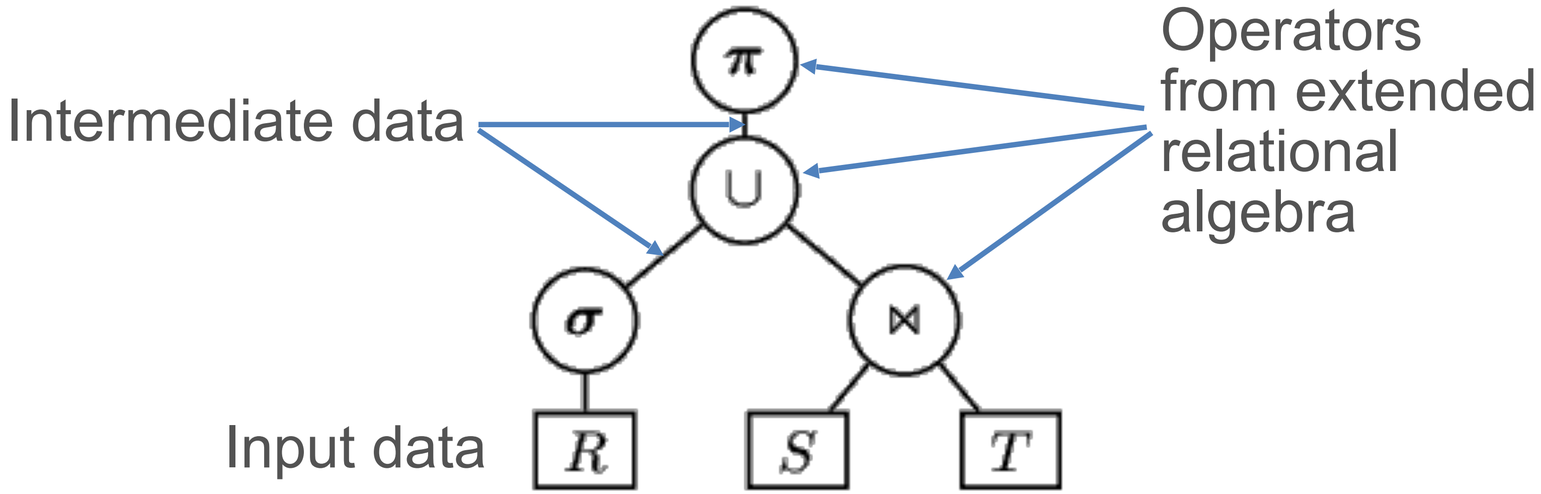

- In multi-core CPUs, a thread uses up 1 core
  - "**Hyper-threading**": Virtualizes a core to run 2 threads

# New Parallelism Concept: Dataflow

- Common in parallel data processing: **“Dataflow Graph”**:
  - A *directed graph* representation of a program with vertices being *abstract operations* from a restricted set of computational primitives:
  - Extended relational dataflows: RDBMS, Pandas, Modin
  - Matrix/tensor dataflows: NumPy, PyTorch, TensorFlow
- Enables us to reason about data-intensive programs at a higher level (logical level?)
- **Task Graph**: Similar but coarse-grained; vertex is a process

# Example Relational Dataflow Graph

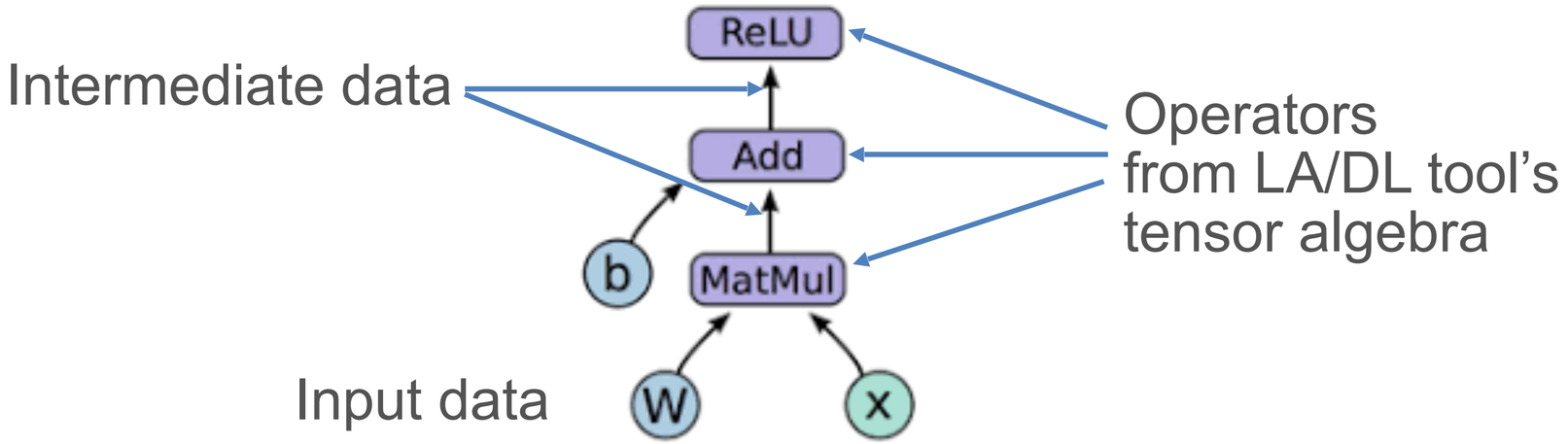
$$\pi(\sigma(R) \cup S \bowtie T)$$




Aka **Logical Query Plan** in the DB systems world

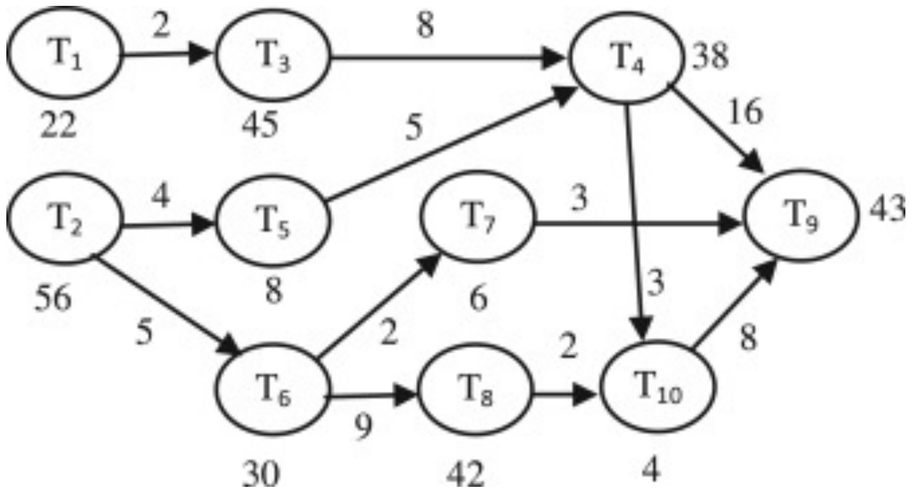
# Example Tensor Dataflow Graph

$$ReLU(WX + b)$$




Aka **Neural Computational Graph** in the ML systems world

# Example Task Graph




- More coarse-grained than operator-level dataflows
- Vertex: A full task/process
- Edge: A dependency between tasks
- Directed Acyclic Graph model (DAG) common; cycles?
- Data may not be shown

**NB:** Dask conflates the concepts of Dataflow and Task graphs because an “operation” on a Dask DataFrame becomes its own separate process/program under the hood!

https://docs.dask.org/en/latest/graphviz.html

# Parallel Data Processing

**Central Issue**: Workload takes too long for one processor!

**Basic Idea**: Split up workload across processors and perhaps also across machines/workers (aka “Divide and Conquer”)

**Key parallelism paradigms in data systems:**

| Dataset is: | **Shared** | **Replicated** | **Partitioned** |
|---|---|---|---|
| **Within a node:** | “SIMD” “Pipelining” | “Task Parallel” Systems | “Data Parallel” Systems |
| **Across nodes:** | N/A |  |  |

# Today's topic: Parallelism

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- DASK
- Single-Node Multi-core; SIMD; Accelerometers

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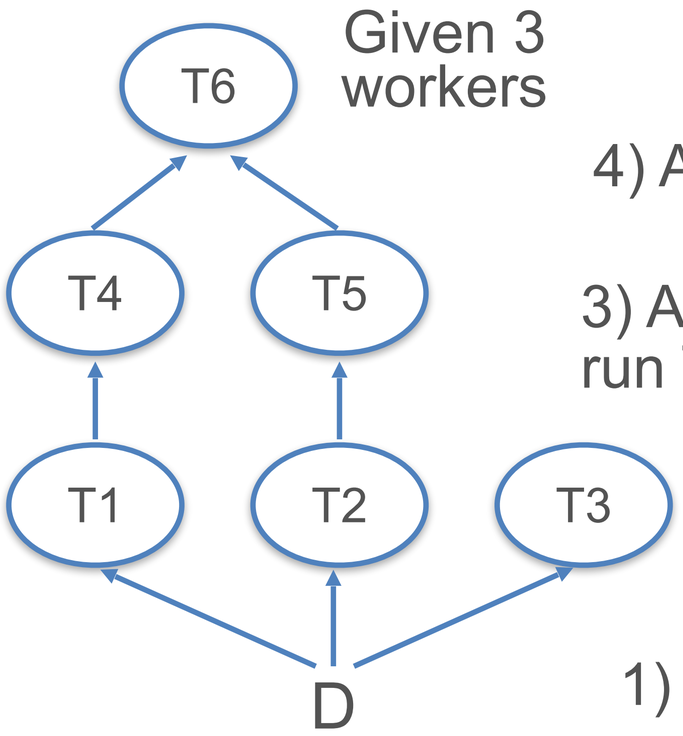
# Task Parallelism

**Basic Idea**: Split up *tasks* across workers; if there is a common dataset that they read, just make copies of it (aka *replication*)

**Example:**




*This is your PA1 setup! Except, Dask Scheduler puts tasks on workers for you.*

4) After T4 & T5 end, run T6 on W1; W2 is *idle*

3) After T1 ends, run T4 on W1; after T2 ends, run T5 on W2; after T3 ends, W3 is *idle*

2) Put T1 on worker 1 (W1), T2 on W2, T3 on W3; run all 3 in parallel

1) Copy whole D to all workers

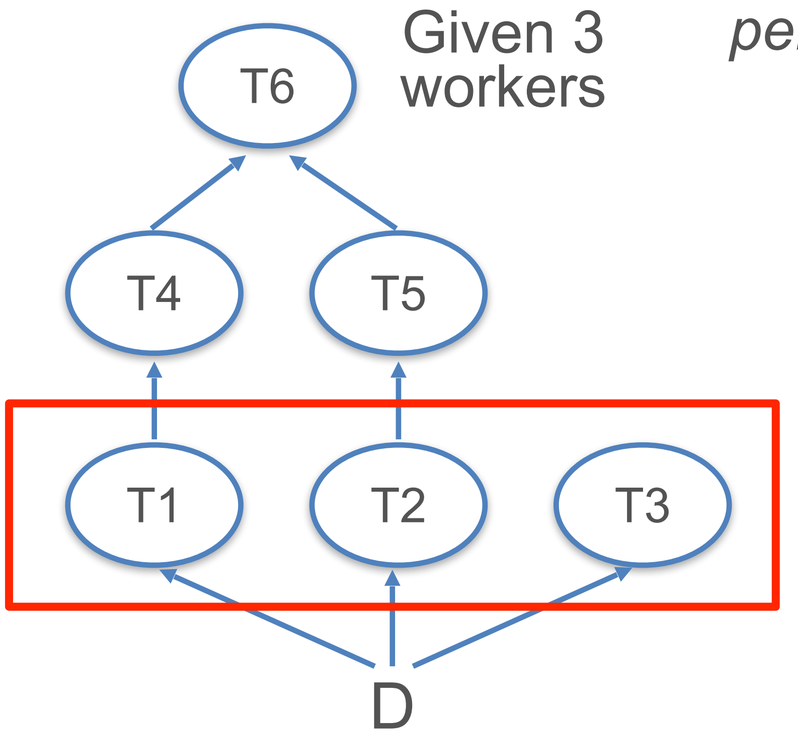
# Task Parallelism

- **Topological sort** of tasks in task graph for scheduling
- Notion of a “worker” can be at processor/core level, not just at node/server level
  - *Thread-level* parallelism possible instead of process-level
  - E.g., Dask: 4 worker nodes x 4 cores = 16 workers total
- **Main pros** of task parallelism:
  - **Simple** to understand; easy to implement
  - **Independence** of workers => low software complexity
- **Main cons** of task parallelism:
  - Data replication across nodes; **wastes memory**/storage
  - **Idle times** possible on workers

# Degree of Parallelism

- The largest amount of *concurrency* possible in the task graph, i.e., how many task can be run simultaneously

**Example:**




***Q:** How do we quantify the runtime performance benefits of task parallelism?*

But over time, degree of parallelism keeps dropping in this example

Degree of parallelism is only 3

So, more than 3 workers is not useful for this workload!

# Quantifying Benefit of Parallelism: Speedup

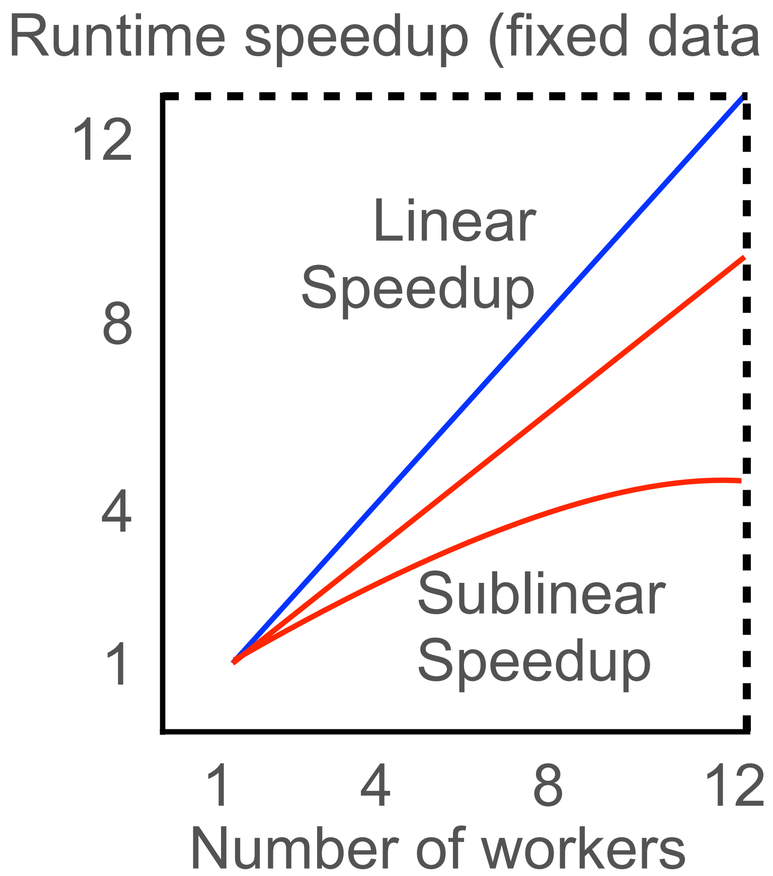
$$\textbf{Speedup} = \frac{\text{Completion time given only 1 worker}}{\text{Completion time given n (>1) workers}}$$

***Q:*** *But given n workers, can we get a speedup of n?*

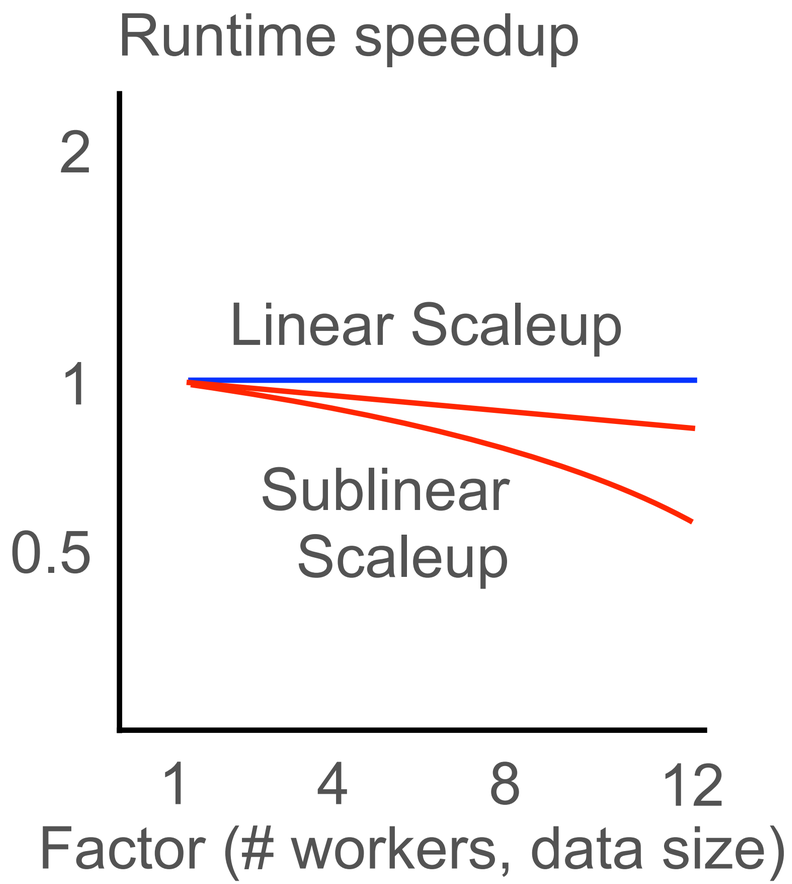
It depends!

(On degree of parallelism, task dependency graph structure, intermediate data sizes, etc.)

# Quantifying Benefit of Parallelism




**Speedup** plot / Strong scaling



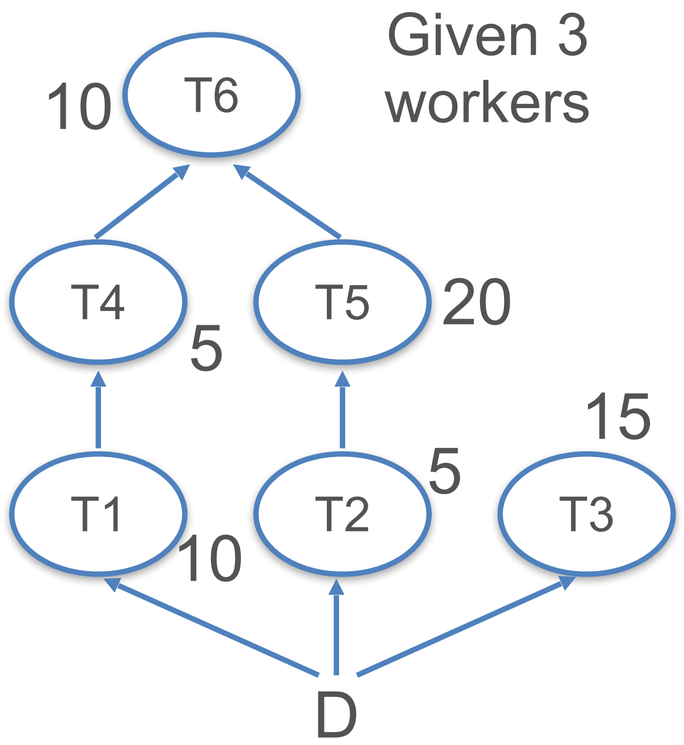

**Scaleup** plot / Weak scaling

***Q:** Is superlinear speedup/scaleup ever possible?*

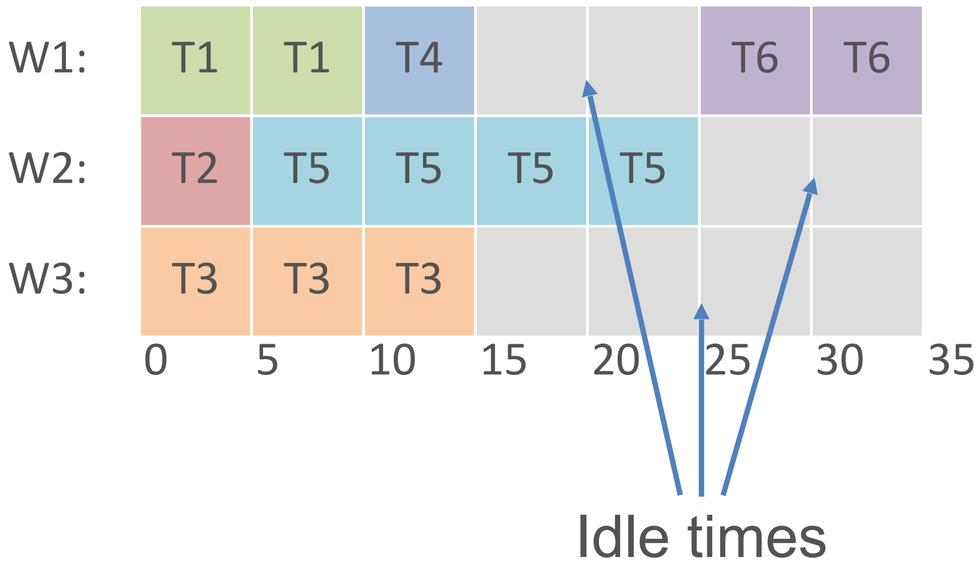
# Idle Times in Task Parallelism

- Due to varying task completion times and varying degrees of parallelism in workload, idle workers waste resources

**Example:**




Gantt Chart visualization of schedule:

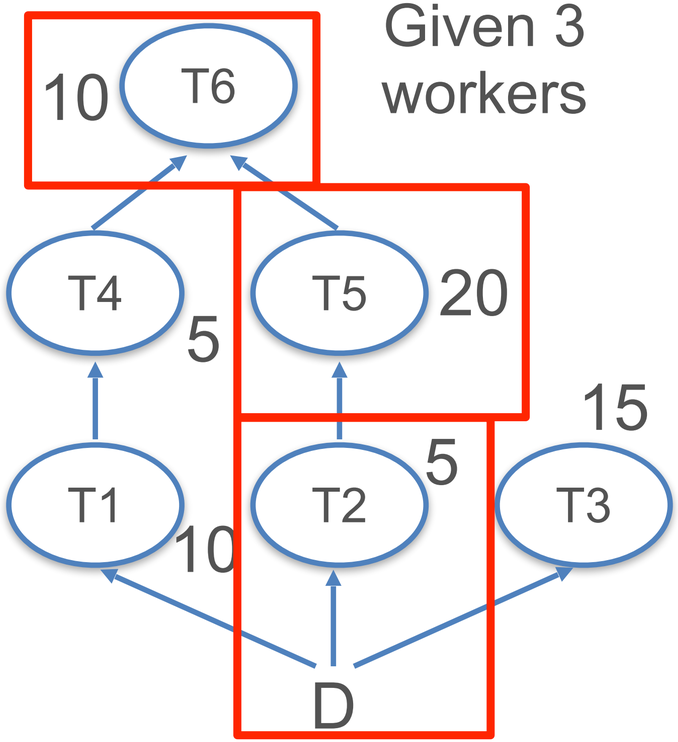


# Idle Times in Task Parallelism

- Due to varying task completion times and varying degrees of parallelism in workload, idle workers waste resources

**Example:**

Given 3 workers

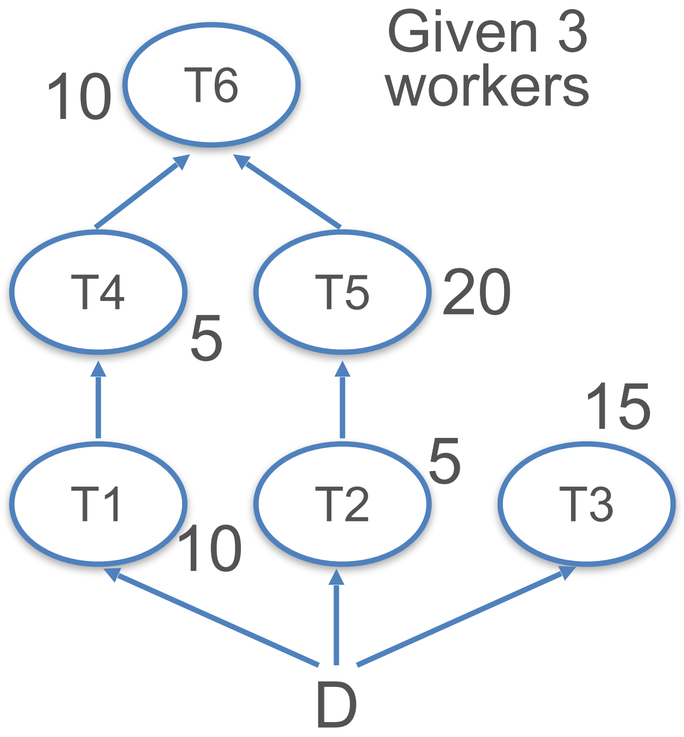



- In general, overall workload's completion time on task-parallel setup is always *lower bounded* by the **longest path** in the task graph
- Possibility: A task-parallel scheduler can "release" a worker if it knows that will be idle till the end
  - Can saves costs in cloud

# Calculating Task Parallelism Speedup

- Due to varying task completion times and varying degrees of parallelism in workload, idle workers waste resources

**Example:**




Completion time with 1 worker: 10+5+15+5+20+10 = 65

Parallel completion time: 35

Speedup = 65/35 = 1.9x

Ideal/linear speedup is 3x

***Q:** Why is it only 1.9x?*

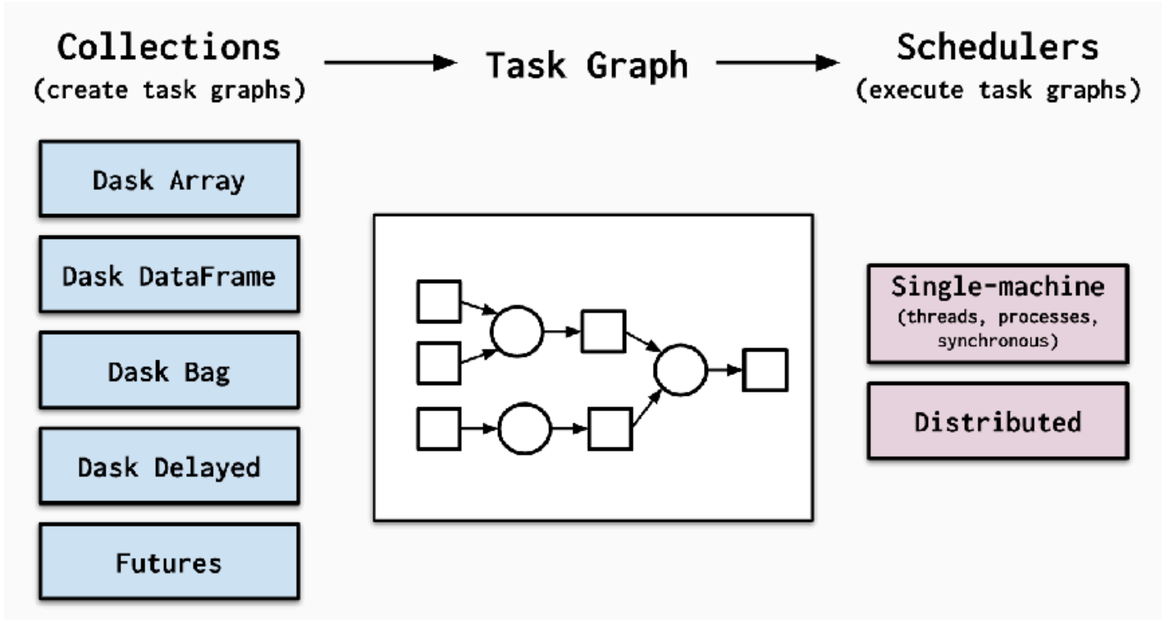
# Task Parallelism in Dask

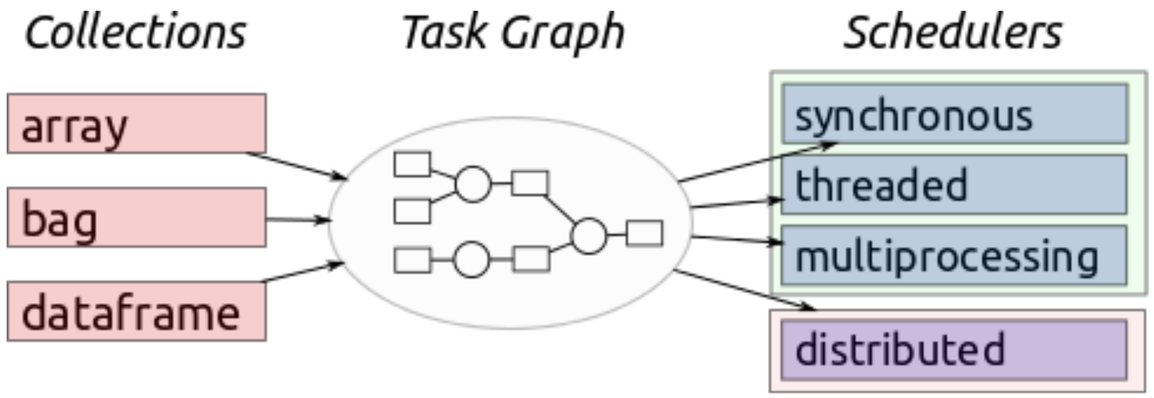
- *“Dask is a flexible library for **parallel** computing in Python”*
- **2 key components:**
  - APIs for data sci. ops on large data
  - Dynamic task scheduling on multi-core/multi-node
- **Design desiderata:**
  - *Pythonic*: Stay within PyData stack (e.g., no JVM)
  - *Familiarity*: Retain APIs of NumPy, Pandas, etc.
  - *Scaling Up*: Seamlessly exploit all cores
  - *Scaling Out*: Easily exploit cluster (needs setup)
  - *Flexibility*: Can schedule custom tasks too
  - *Fast?*: “Optimized” implementations under APIs



https://docs.dask.org/en/latest/

# Task Parallelism in Dask




https://docs.dask.org/en/latest/
https://docs.dask.org/en/latest/scheduling.html

# Dask's Workflow

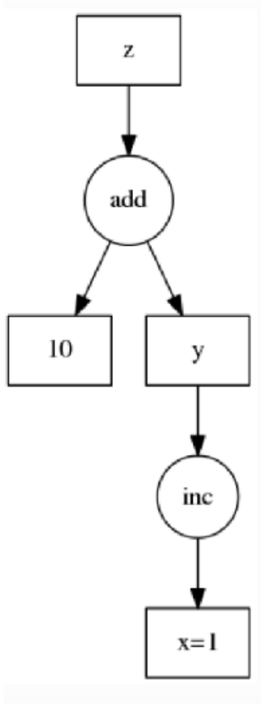
- **"Lazy Evaluation":**
  - Ops on data struct. are NOT executed immediately
  - Triggered manually, e.g., *compute()*
  - Dataflow graph / task graph is built under the hood

```
def inc(i):
    return i + 1

def add(a, b):
    return a + b

x = 1
y = inc(x)
z = add(y, 10)
```

User code using their API

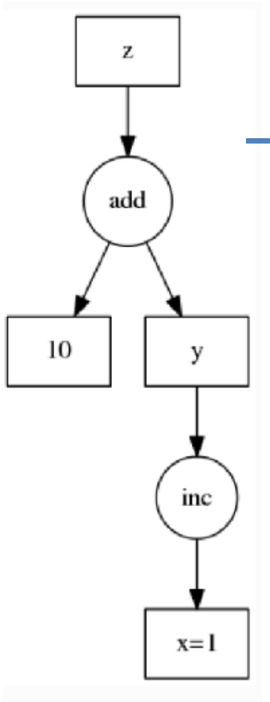
```
d = {'x': 1,
     'y': (inc, 'x'),
     'z': (add, 'y', 10)}
```

Internal dictionary with key-value pair representation of dataflow/task graph



# Dask's Workflow

- Rest of the Dask's workflow for distributing computations:




"Optimize" Task Graph

Serialize Task Graph (dictionary)

Communicate it to Scheduler

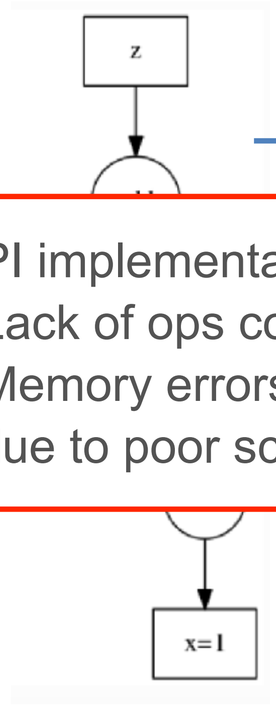
Scheduler divvies up work for cores/nodes

Each worker does its job and notifies Scheduler

https://docs.dask.org/en/latest/phases-of-computation.html

# Possible Bottlenecks/Issues in Dask

- Rest of the Dask's workflow for distributing computations:




API implementation:
- Lack of ops coverage
- Memory errors in ops due to poor scalability

"Optimize" Task Graph

Poor/missed optimizations

Serialize Task Graph (dictionary)

Huge task graphs take too long to serialize and/or communicate

Scheduler divvies up work for cores/nodes

Poor scalability of Scheduler

Each worker does its job and notifies Scheduler

Machine/network failures

# Best Practices for Task-Par. Dask

- **Tuning task graph sizes:**
  - Avoid too many tasks (ser./comm./sched. bottlenecks) but also avoid too few tasks (under-utilization of cores/nodes)
  - Be mindful of available # cores/nodes
- Rough guidelines they give:
  - Adjust # tasks by fusing ops/tasks (aka “**batching**”) vs. breaking up ops/tasks
  - Adjust # tasks by tuning data chunk size (next slide)
- **Use the Diagnostics dashboard:**
  - Monitor # tasks, core/node usage, task completion

https://docs.dask.org/en/latest/best-practices.html
https://docs.dask.org/en/latest/diagnostics-distributed.html

# Best Practices for Task-Par. Dask

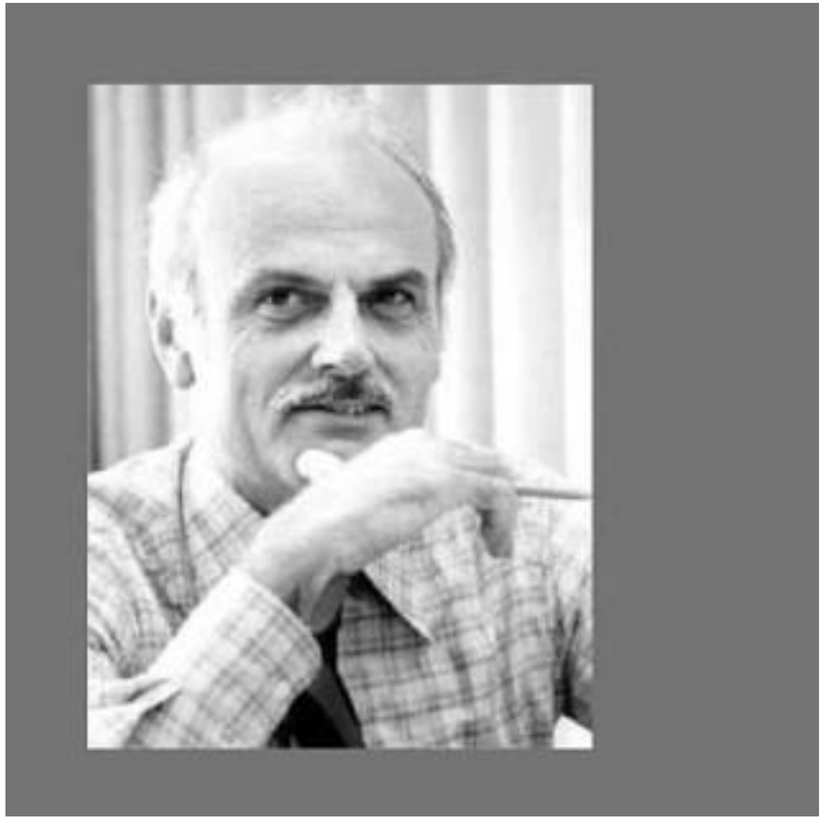
- **Tuning data chunk sizes:**
  - Avoid too few chunks (low degree of par.) but also too many chunks (task graph overhead)
  - Be mindful of available DRAM
- Rough guidelines they give:
  - # data chunks ~ 3x-10x # cores, but
  - # cores x chunk size must be < machine DRAM, but
  - chunk size should not be too small either (~1 GB is OK)

***Q:*** *Do you tune any of these when using an RDBMS? :)*

Dask still lacks “physical data independence”!

https://docs.dask.org/en/latest/best-practices.html

# The WRATH of Codd?



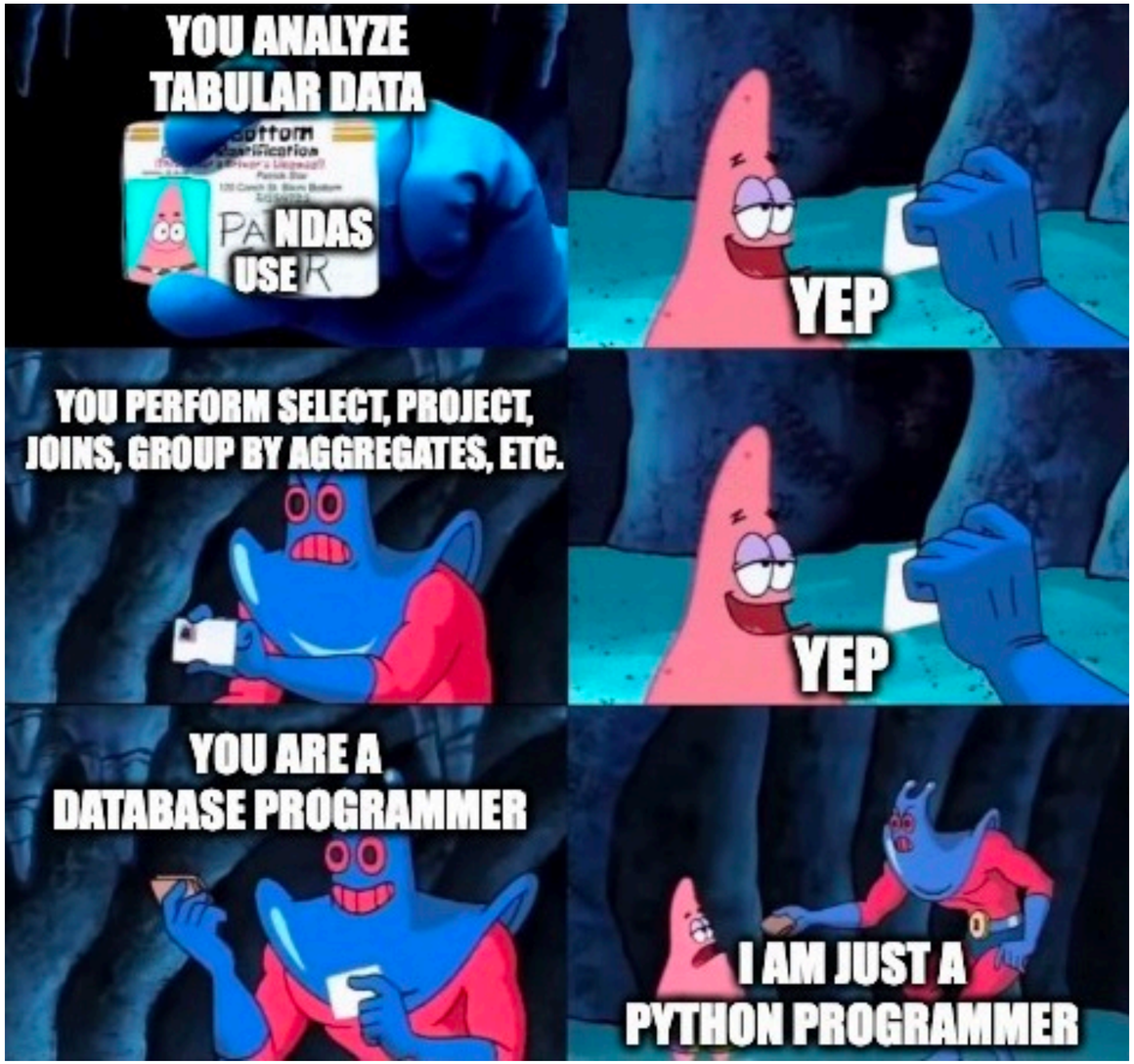
*Information Retrieval*

## A Relational Model of Data for Large Shared Data Banks

E. F. Codd
*IBM Research Laboratory, San Jose, California*

Future users of large data banks must be protected from having to know how the data is organized in the machine (the internal representation). A prompting service which supplies such information is not a satisfactory solution. Activities of users at terminals and most application programs should remain unaffected when the internal representation of data is changed and even when some aspects of the external representation are changed. Changes in data representation will often be needed as a result of changes in query, update, and report traffic and natural growth in the types of stored information.

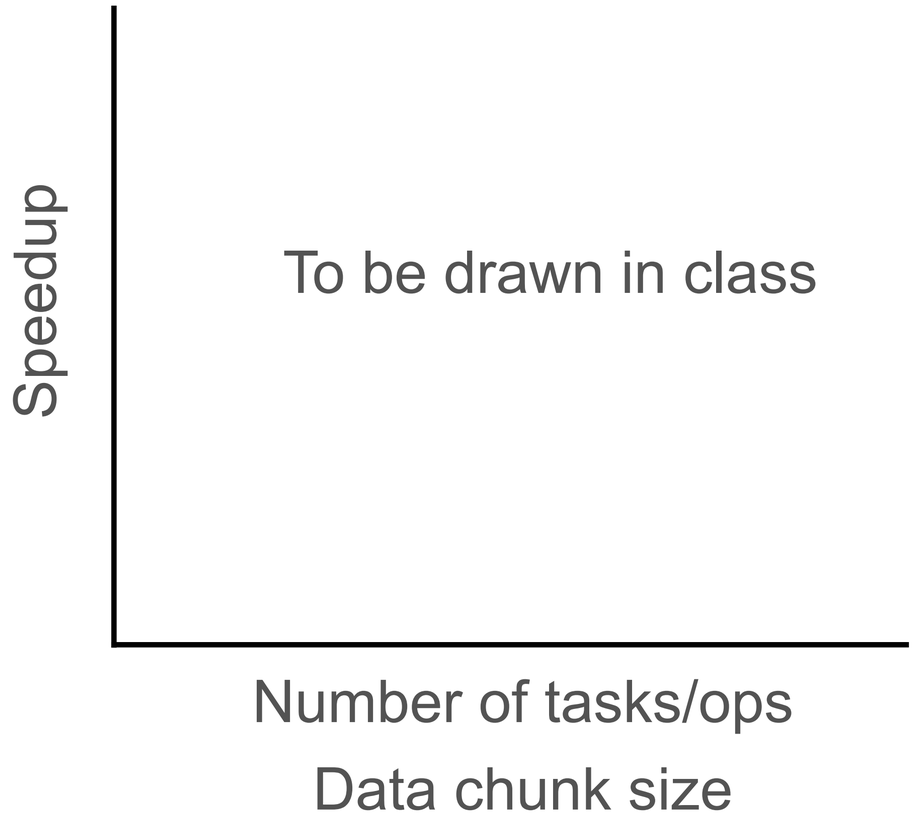
# Y’all are database programmers! :)




https://datasystemsfun.tumblr.com/post/678558379303731200/some-pandas-users-be-like-xd

# Execution Optimization Tradeoffs

- Be judicious in batching ops vs. breaking up tasks
- Be judicious in tuning data chunk sizes



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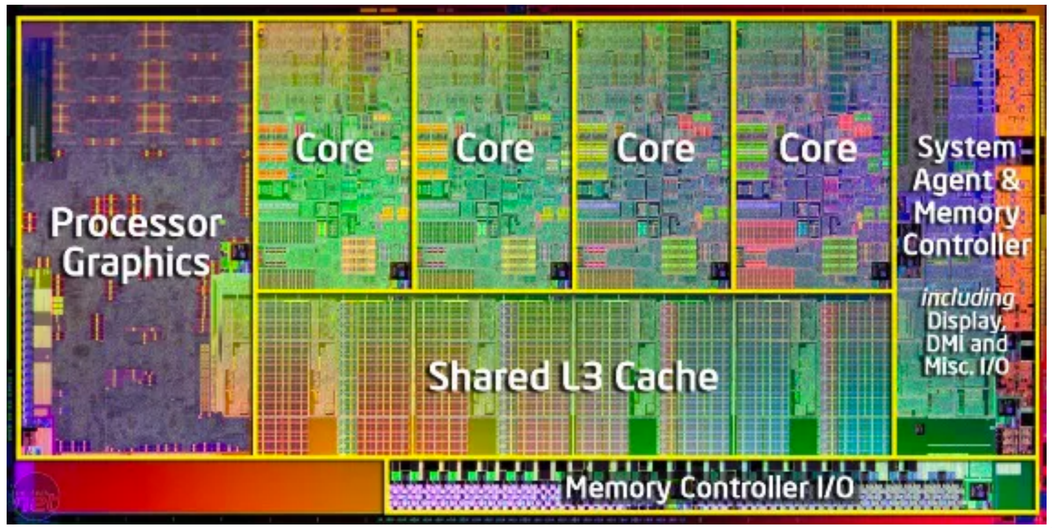
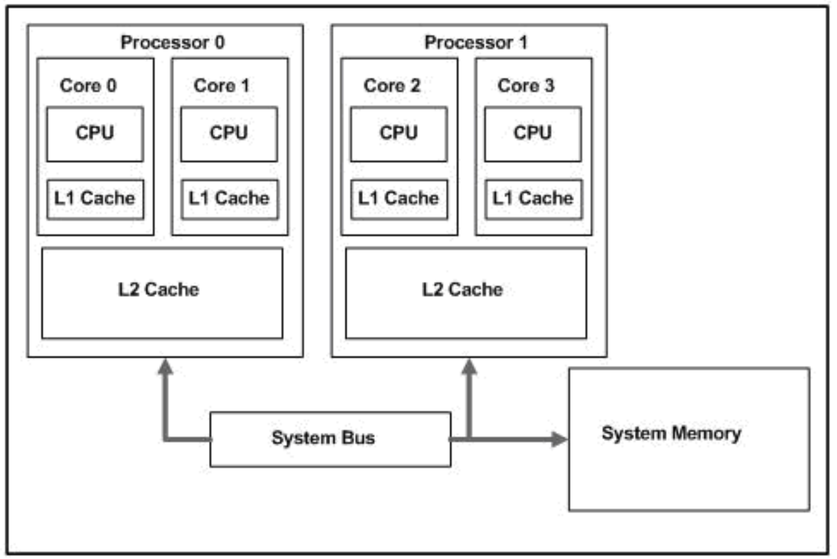
# Multi-core CPUs

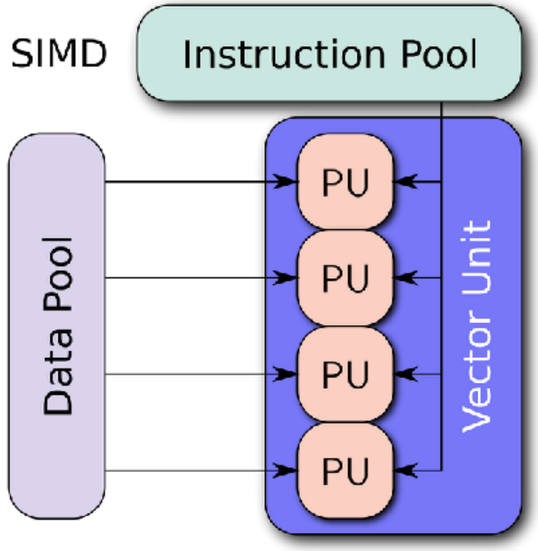
- Modern computers often have multiple processors and multiple *cores* per processor, with a hierarchy of shared caches
- OS Scheduler controls what cores/processors assigned to what processes/threads when



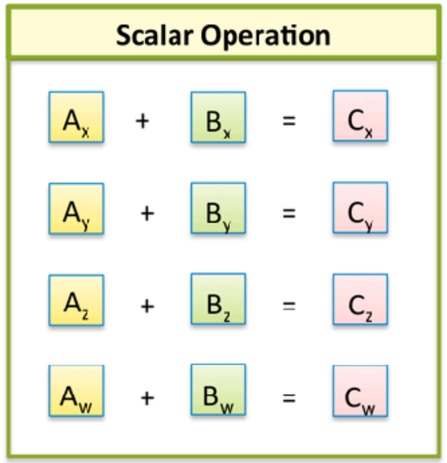



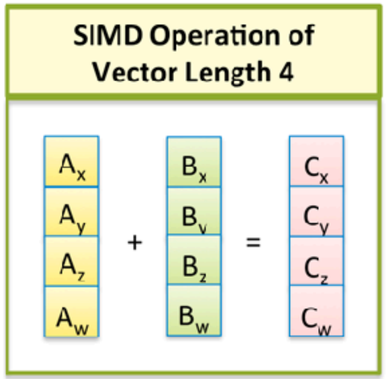
# Single-Instruction Multiple-Data

- **Single-Instruction Multiple-Data (SIMD):** A fundamental form of parallel data processing in which *different chunks of data* are processed by the *"same" set of instructions* shared by multiple processing units (PUs)
- Aka "vectorized" instruction processing (vs "scalar")
- Data science workloads are very amenable to SIMD




**Example for SIMD in data science:**



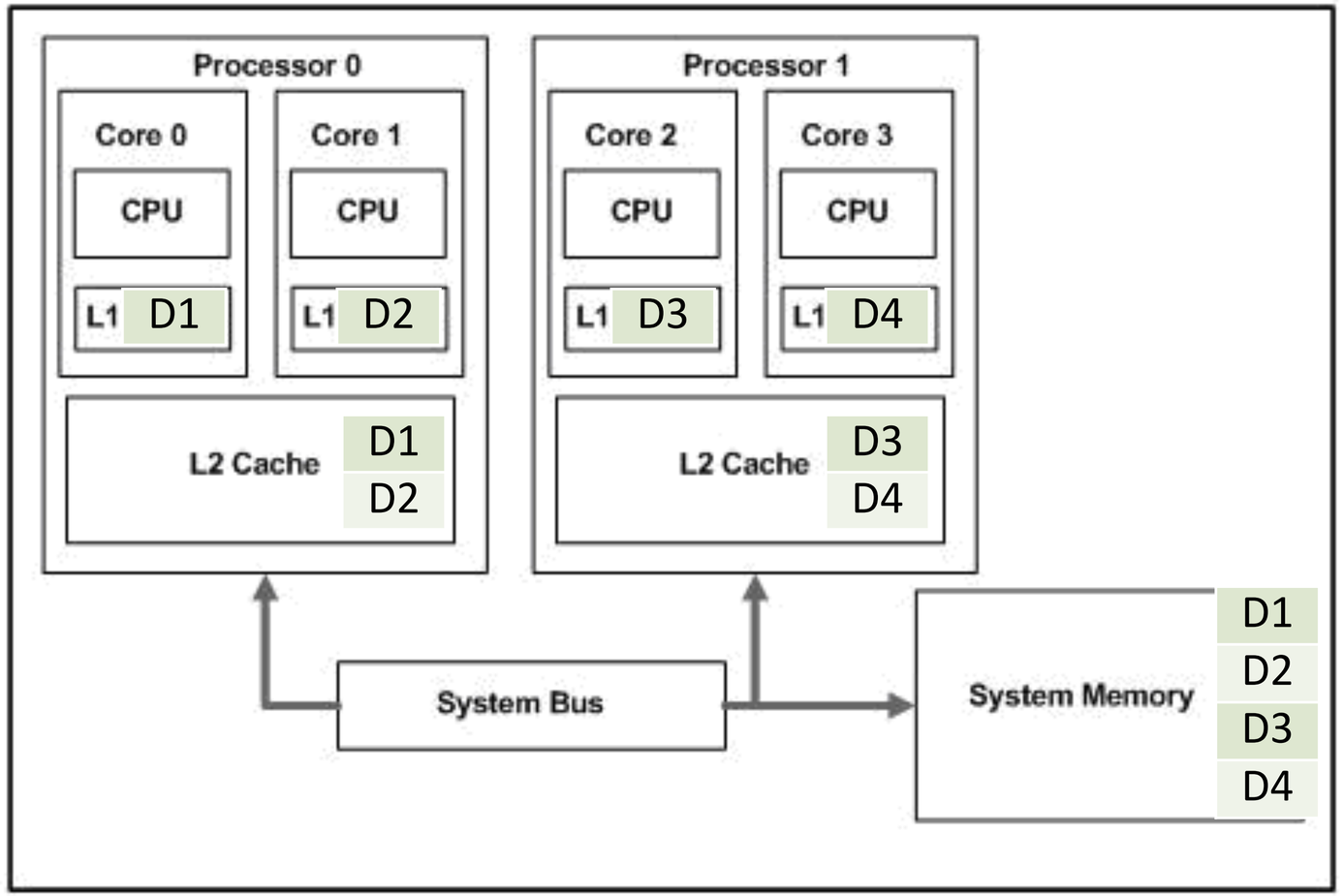




Intel® Architecture currently has SIMD operations of vector length 4, 8, 16

# SIMD Generalizations

- **Single-Instruction Multiple Thread (SIMT):** Generalizes notion of SIMD to *different threads* concurrently doing so
  - Each thread may be assigned a core or a whole PU
- **Single-Program Multiple Data (SPMD):** A higher level of abstraction generalizing SIMD operations or programs
  - Under the hood, may use multiple processes or threads
  - Each chunk of data processed by one core/PU
  - Applicable to any CPU, not just vectorized PUs
  - Most common form of parallel data processing at scale

# “Data Parallel” Multi-core Execution



# Quantifying Efficiency: Speedup

***Q:*** *How do we quantify the runtime performance benefits of multi-core parallelism?*

- As with task parallelism, we measure the speedup:

$$\textbf{Speedup} = \frac{\text{Completion time given only 1 core}}{\text{Completion time given n (>1) core}}$$

- In data science computations, a useful surrogate for completion time is the instruction throughput: **FLOPS**, i.e., *number of FLoating point OPerations per Second*
- Modern data processing programs, especially deep learning (DL) may have billions of FLOPs aka GFLOPs!

# Amdahl's Law

***Q:*** *But given n cores, can we get a speedup of n?*

It depends! (Just like it did with task parallelism)

- **Amdahl's Law:** Formula to upper bound possible speedup
  - A program has 2 parts: one that benefits from multi-core parallelism and one that does not
  - Non-parallel part could be for control, memory stalls, etc.

1 core: n cores:

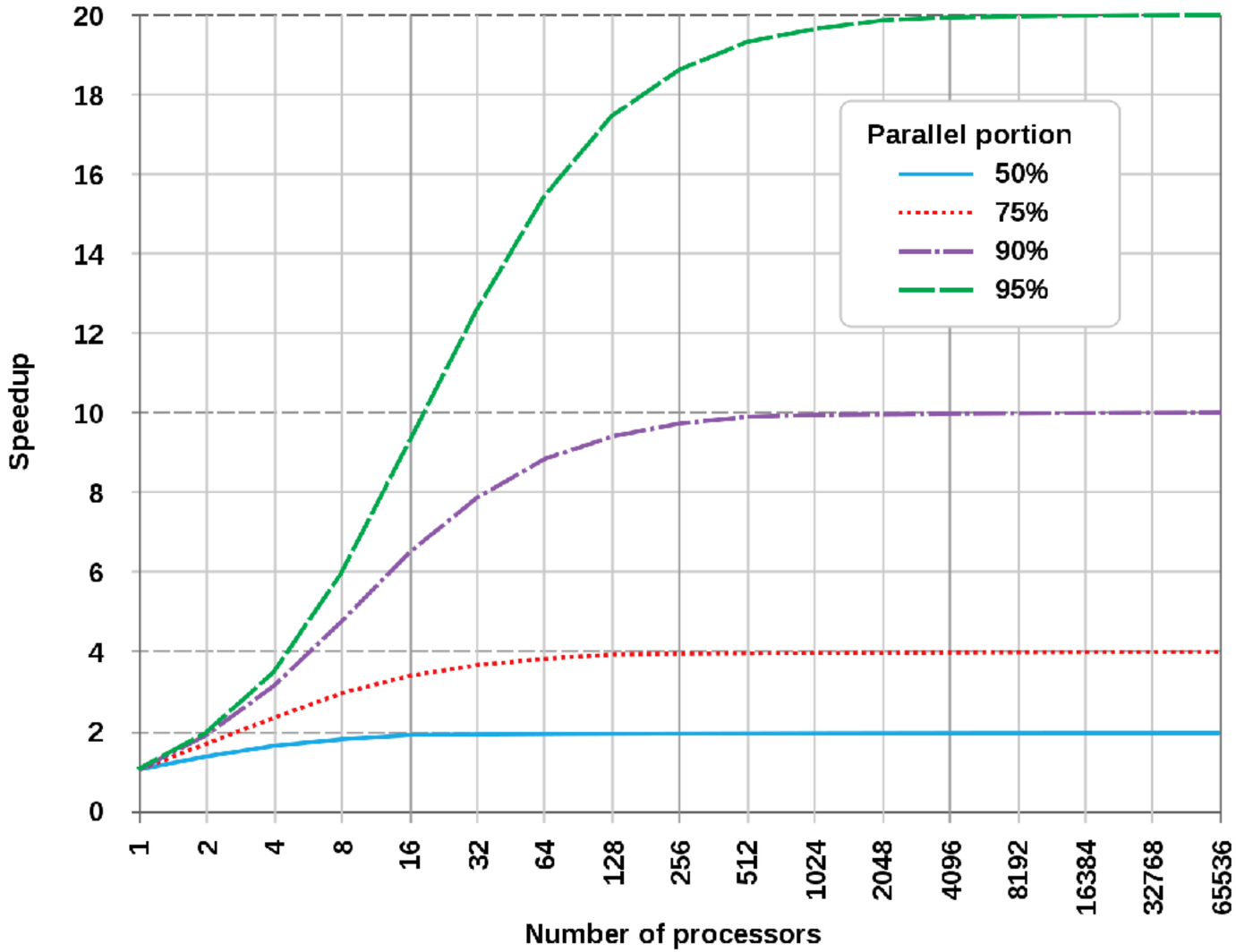
$T_{yes} \longrightarrow T_{yes}/n$

$T_{no} \longrightarrow T_{no}$

$$\text{Speedup} = \frac{T_{yes} + T_{no}}{T_{yes}/n + T_{no}} = \frac{n(1 + f)}{n + f}$$

Denote $T_{yes}/T_{no} = f$

# Amdahl's Law



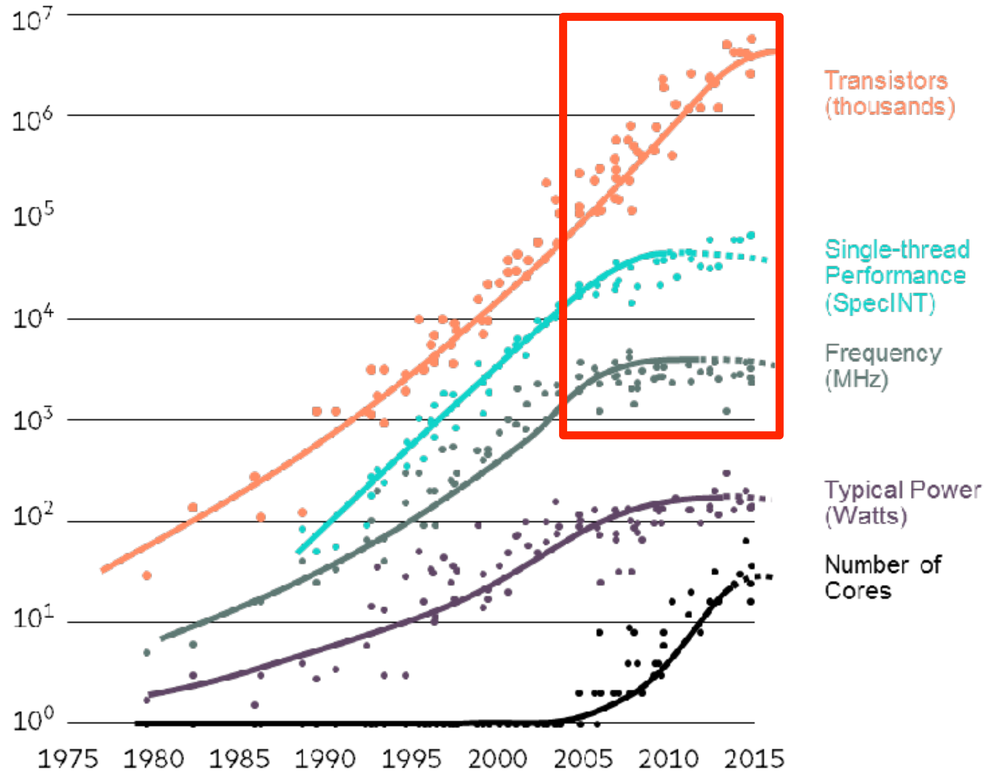

$f = T_{yes}/T_{no}$

Parallel portion = $f / (1 + f)$

Speedup = $\frac{n(1 + f)}{n + f}$

# Hardware Trends on Parallelism

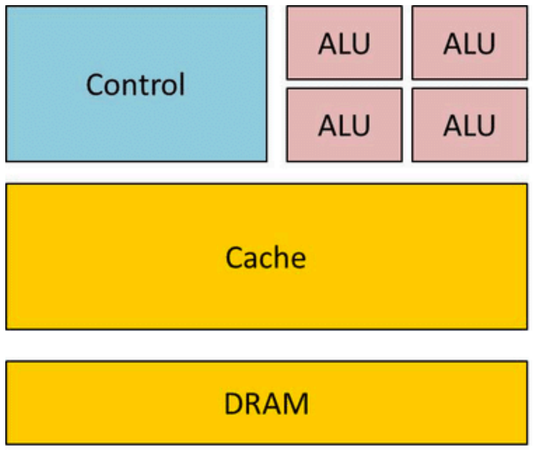
- Multi-core CPUs grew rapidly in early 2000s but hit physical limits due to packing efficiency and power issues
- End of “Moore’s Law” and End of “Dennard Scaling”



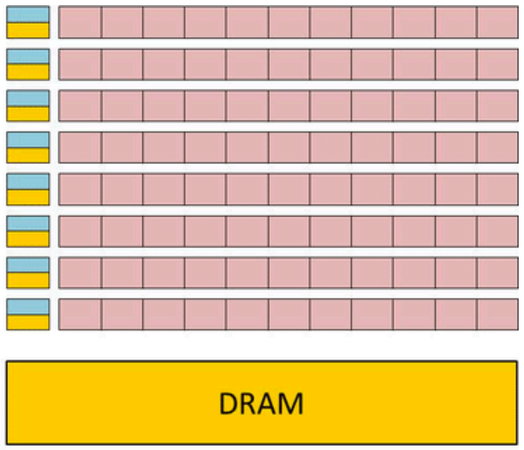

- Takeaway from hardware trends: it is hard for general-purpose CPUs to sustain FLOPs-heavy programs like deep nets
- Motivated the rise of “accelerators” for some classes of programs

# Hardware Accelerators: GPUs

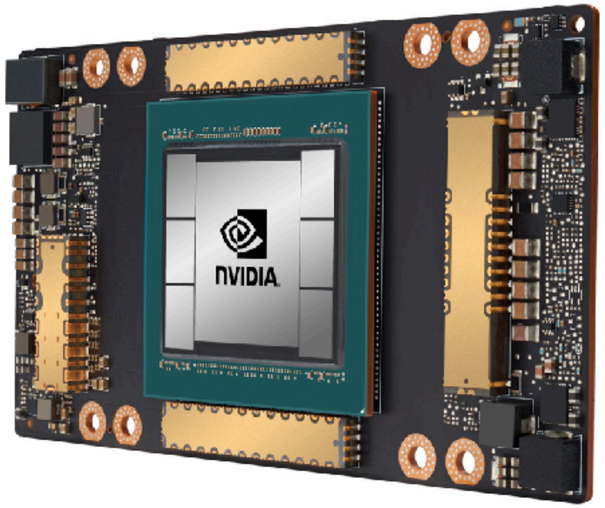
- **Graphics Processing Unit (GPU)**: Tailored for matrix/tensor ops
- Basic idea: Use tons of ALUs; massive data parallelism (SIMD on steroids); now A100 offers ~20 TFLOPS for FP32!
- Popularized by NVIDIA in early 2000s for video games, graphics, and multimedia; now ubiquitous in DL
- CUDA released in 2007; later wrapper APIs on top: CuDNN, CuSparse, CuDF (RapidsAI), etc.



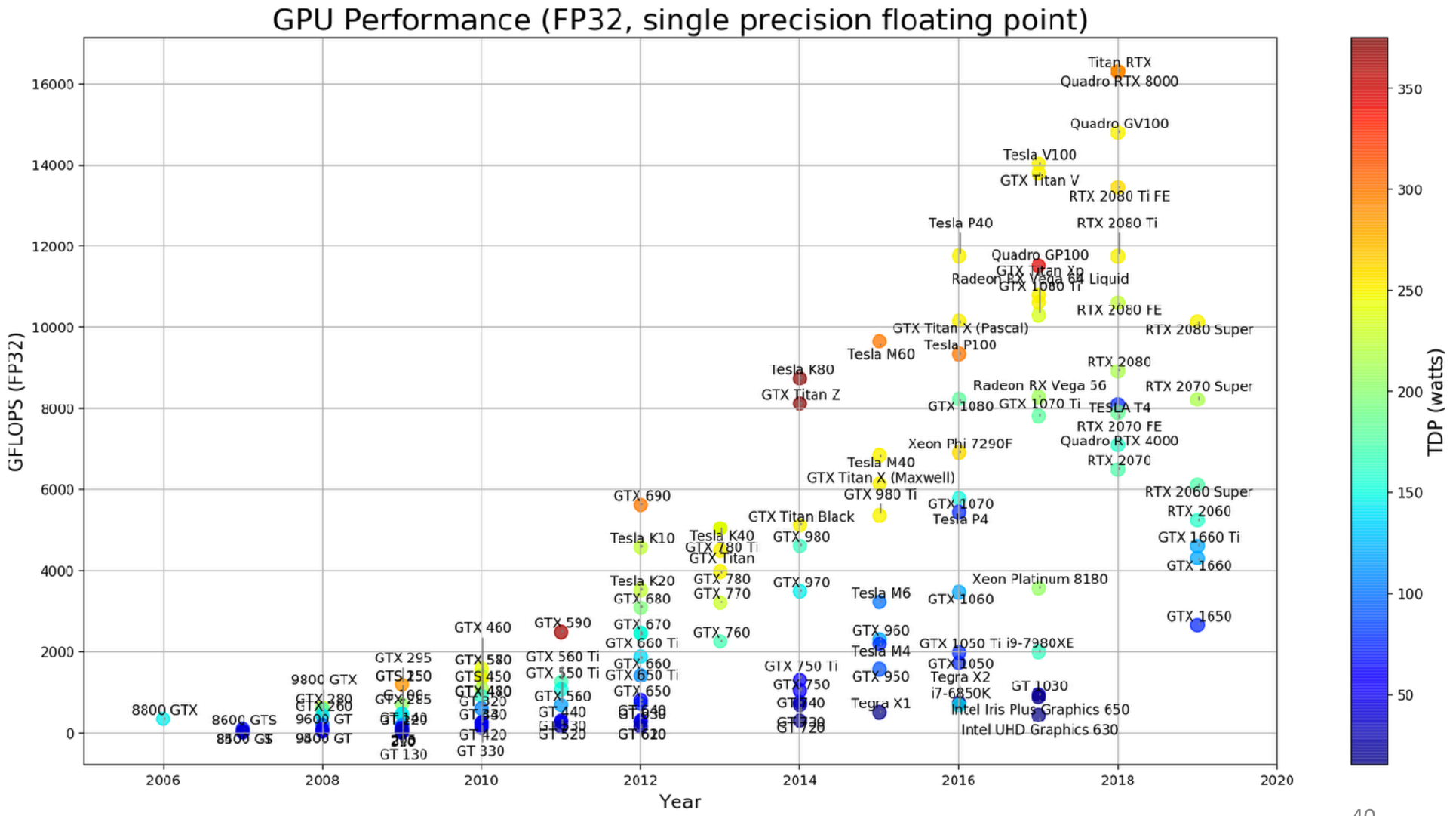

CPU




GPU

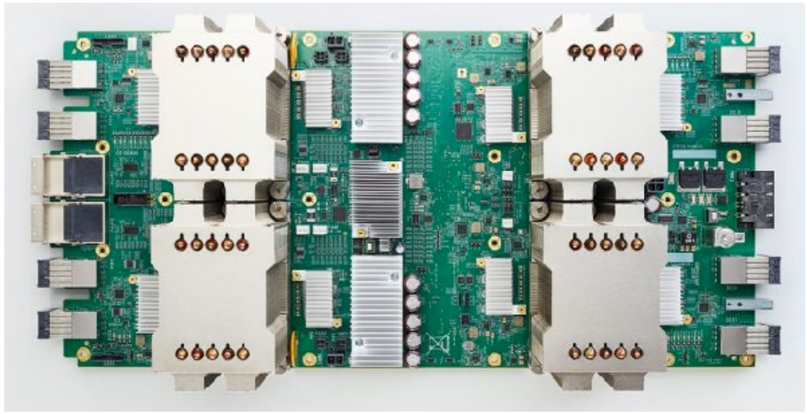


# GPUs on the Market



# Other Hardware Accelerators

- **Tensor Processing Unit (TPU):**
  - An “application-specific integrated circuit” (ASIC) created by Google in mid 2010s; used for AlphaGo
  - Even more specialized tensor ops in DL inference; ~45 TFLOPS!
- **Field-Programmable Gate Array (FPGA):**
  - Configurable for *any* class of programs; ~0.5-3 TFLOPS but very low power consumption
  - Cheaper; new hardware-software integrated stacks for ML/DL



# Comparing Modern Parallel Hardware

| | Multi-core CPU | GPU | FPGA | ASICs (e.g., TPUs) |
|---|---|---|---|---|
| **Peak FLOPS** | Moderate | High | High | Very High |
| **Power Consumption** | High | Very High | Very Low | Low-Very Low |
| **Cost** | Low | High | Very High | Highest |
| **Generality / Flexibility** | Highest | Medium | Very High | Lowest |
| **Fitness for DL Training?** | Poor Fit | Best Fit | Poor Fit | Potential exists but not mass market |
| **Fitness for DL Inference?** | Moderate | Moderate | Good Fit | Best Fit |
| **Cloud Vendor Support** | All | All | All | GCP |



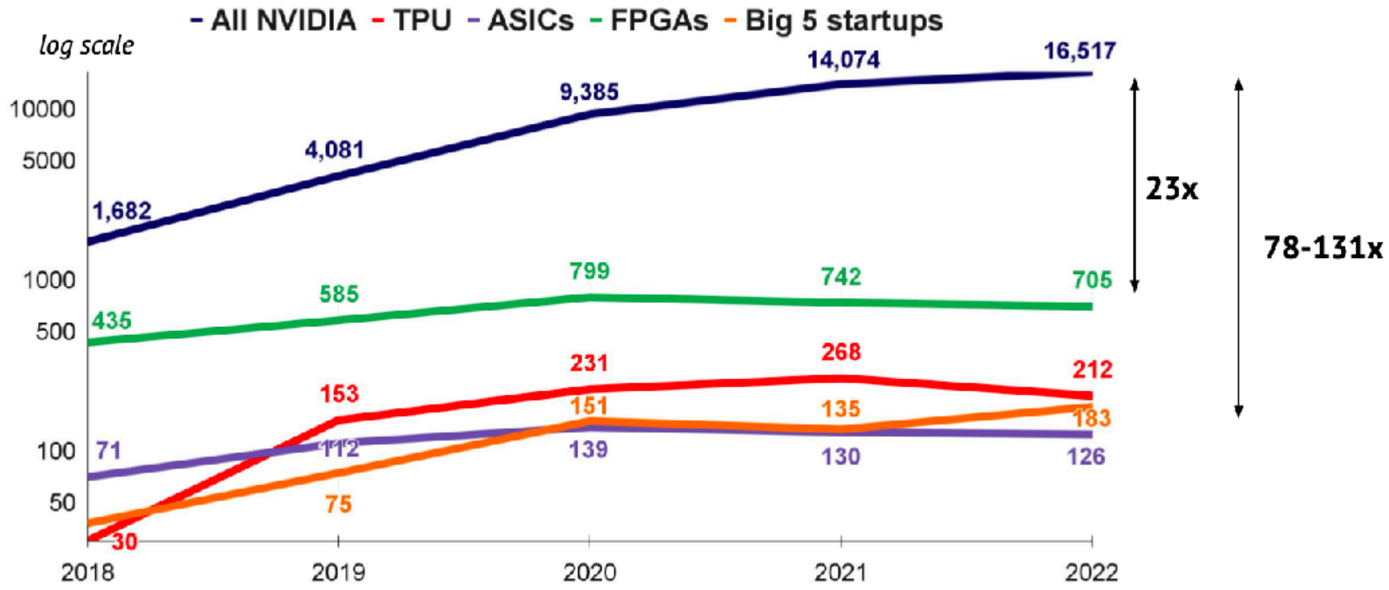
https://www.embedded.com/leveraging-fpgas-for-deep-learning/

# NVIDIA's monopoly remains strong!



**NVIDIA's chips are the most popular in AI research papers...and by a massive margin**

- **GPUs are 131x more commonly used than ASICs, 90x more than chips from Graphcore, Habana, Cerebras, SambaNova and Cambricon combined, 78x more than Google's TPU, and 23x more than FPGAs.**




Zeta Alpha

stateof.ai 2022



https://www.stateof.ai/

# Review Questions

- Briefly explain 3 benefits of large-scale data in Data Science.
- What is a dataflow graph? Give an example from a data system.
- How does a task graph differ from a dataflow graph?
- Briefly explain 1 pro and 1 con of task parallelism.
- Briefly explain 1 scalability bottleneck that Dask still faces.
- What is the degree of parallelism of a task graph?
- What is speedup? How is it different from scaleup?
- Is linear speedup always possible with task parallelism?
- What is SIMD? Why is “vectorized” data processing critical?
- What is the point of Amdahl’s Law?
- Briefly 1 pro and 1 con of TPU vs. GPU.