Data-Intensive Distributed Computing
CS 451/651 (Fall 2025)

Batch Processing I
(v1.01)

Week 3: September 16

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These slides are available at `https://lintool.github.io/cs451-2025f/`

Key Questions

What's the difference between scaling up and scaling out?

What are the implications of distributed processing across many machines?

What are the challenges for a divide-and-conquer strategy?

What challenges does partitioning address?
What challenges does it exacerbate?

What challenges does replication address?
What challenges does it exacerbate?

What's MapReduce and how does it work with HDFS?

What are we trying to do?
tl;dr – everything!

You want

Flexible tools
Diverse data and workloads
High scalability and elasticity
Low latency, high throughput
…

Your boss wants

Cheap
Easy to manage
Small environmental footprint
…

Remember: There are no solutions, only tradeoffs!

Example

Is saving 1.27ms in latency worth $1billion dollars?

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

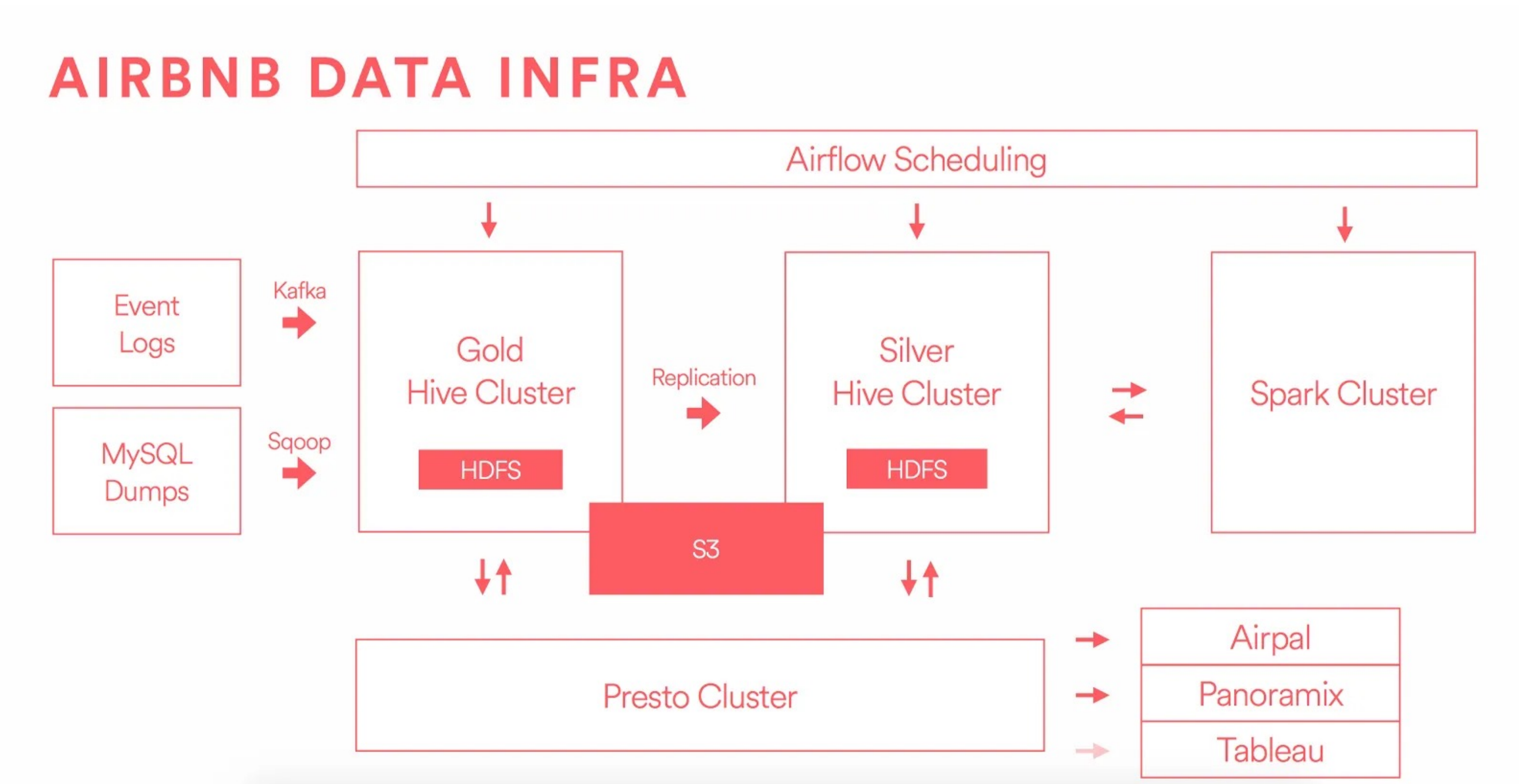
Trick #1: Partition

Trick #2: Replicate

Remember: There are no solutions, only tradeoffs!

Immutable Truth #1: At scale, you must distribute work across multiple machines.

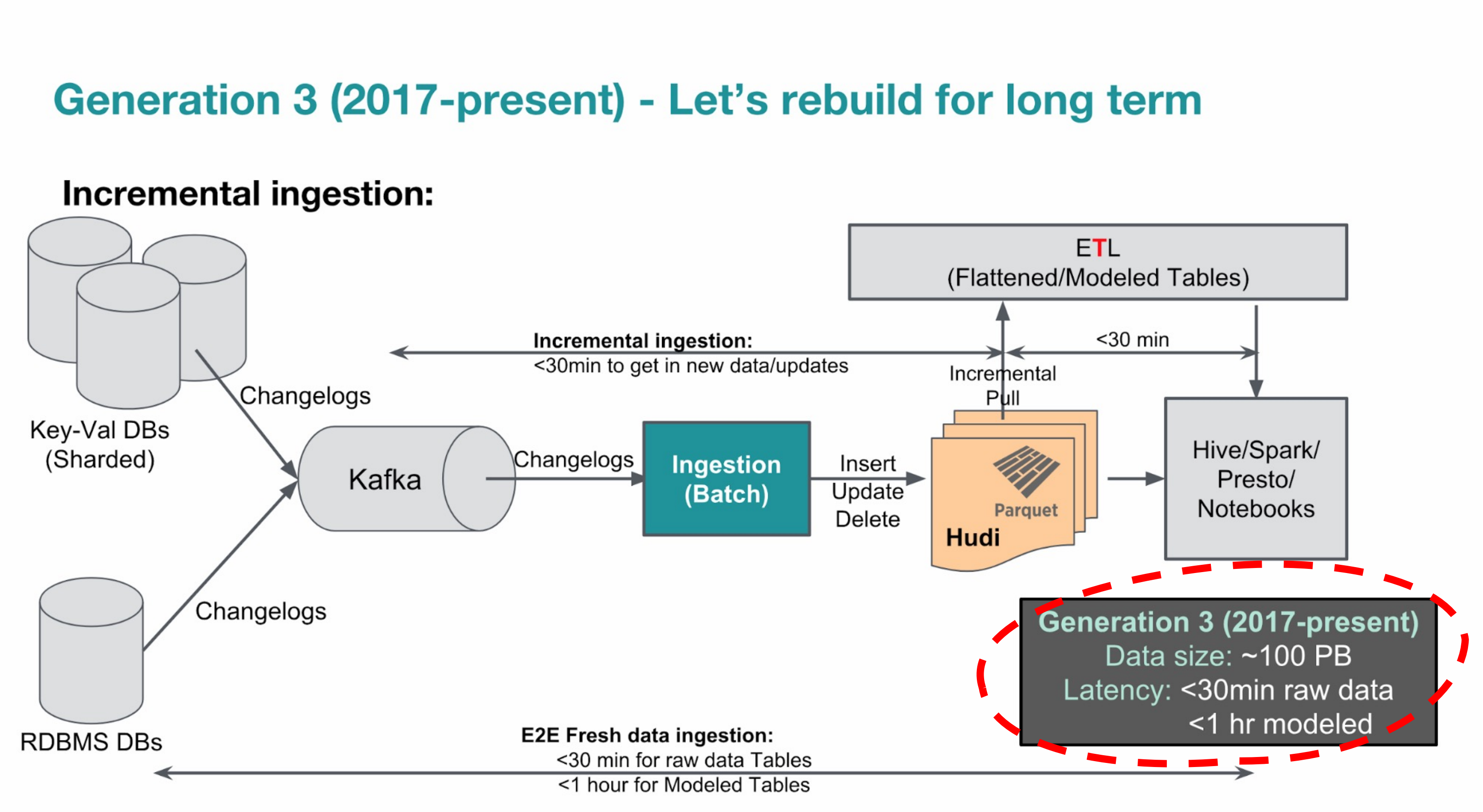
Obvious?



To set some context for scale, two years ago we moved from Amazon EMR onto a set of EC2 instances running HDFS with 300 terabytes of data. Today, we have two separate HDFS clusters with 11 petabytes of data and we also store multiple petabytes of data in S3 on top of that.

AirBnB's data platform (circa 2016)

https://medium.com/airbnb-engineering/data-infrastructure-at-airbnb-8adfb34f169c



Uber's data platform (circa 2018)

https://www.uber.com/en-CA/blog/uber-big-data-platform/

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Obvious?

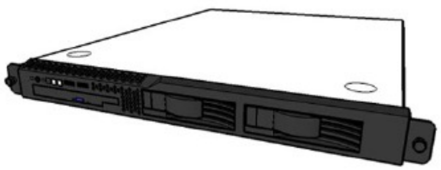
Scale-out vs. Scale-up

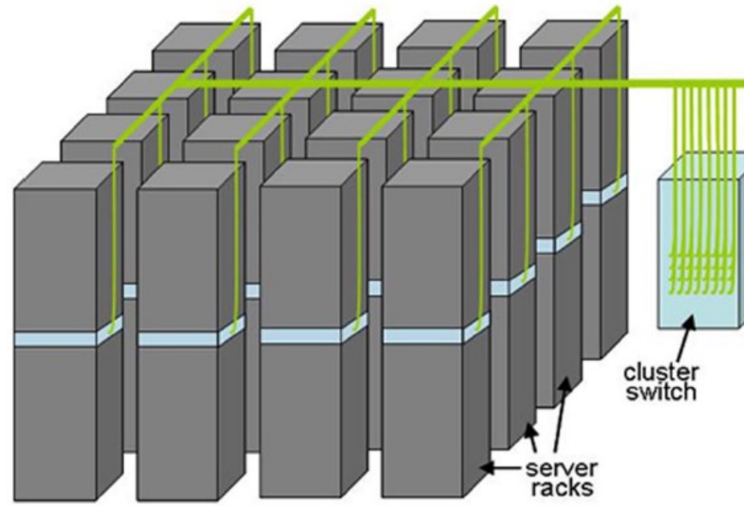
… but don't under-estimate the power of a single "beefy" machine

GCP `x4-megamem-1920-metal` instance:
1920 vCPUs, 32,768 GB RAM, 512 TiB disk

https://cloud.google.com/compute/docs/memory-optimized-machines

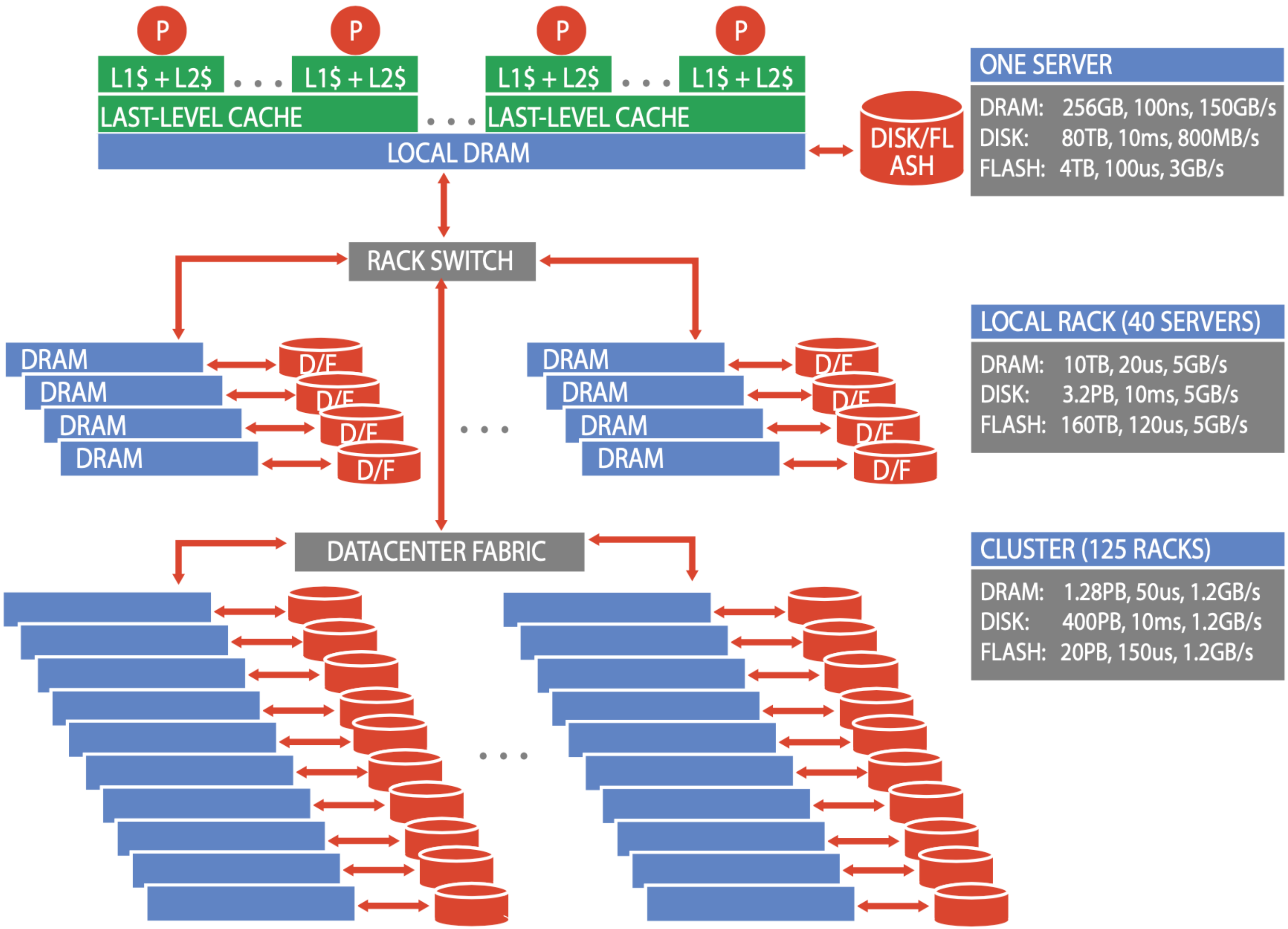
Building Blocks





Source: Barroso and Urs Hölzle (2009)

Datacenter Organization



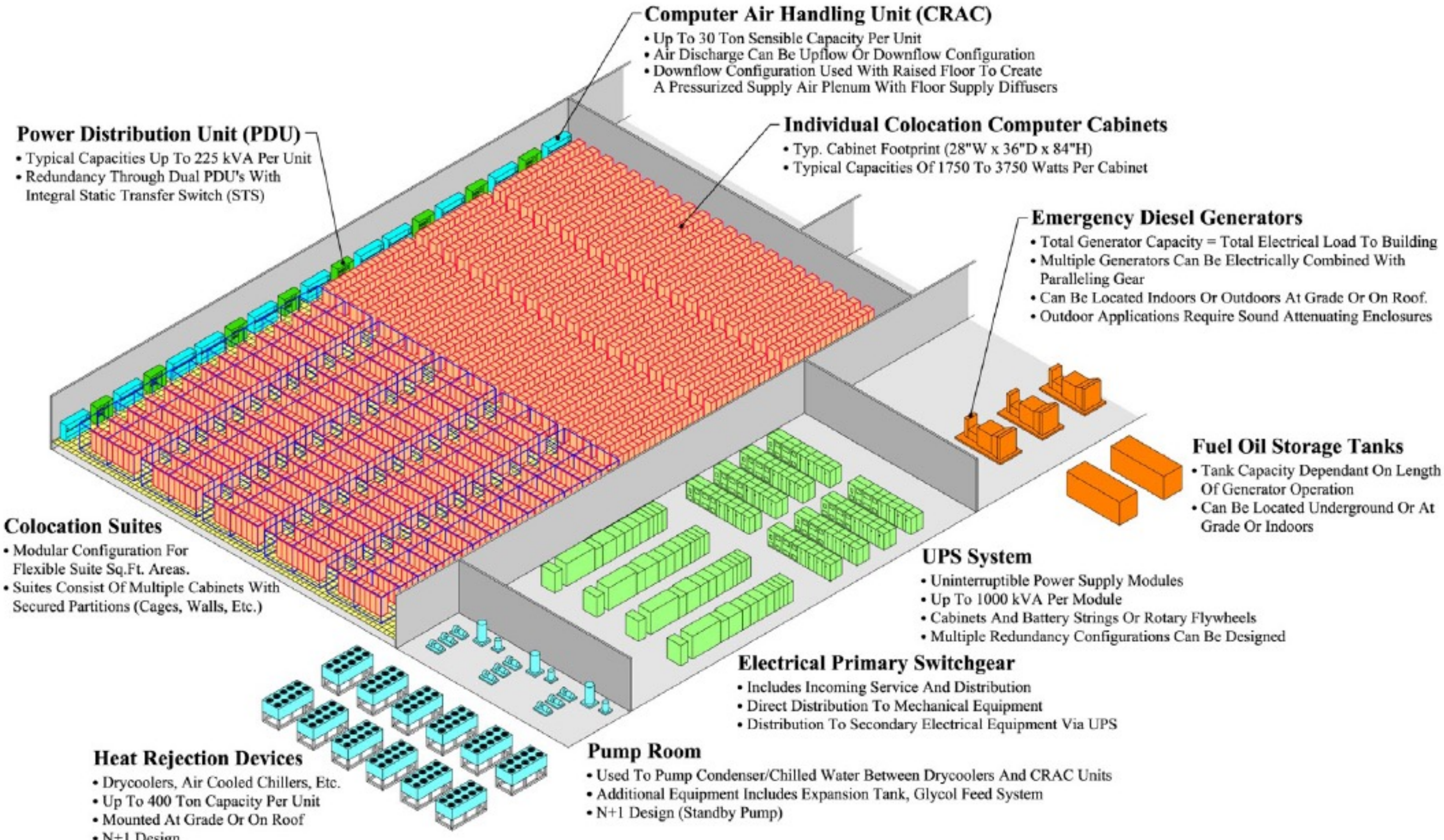
Source: Barroso et al. (2019)

Source: Google

Source: Google

Source: Facebook

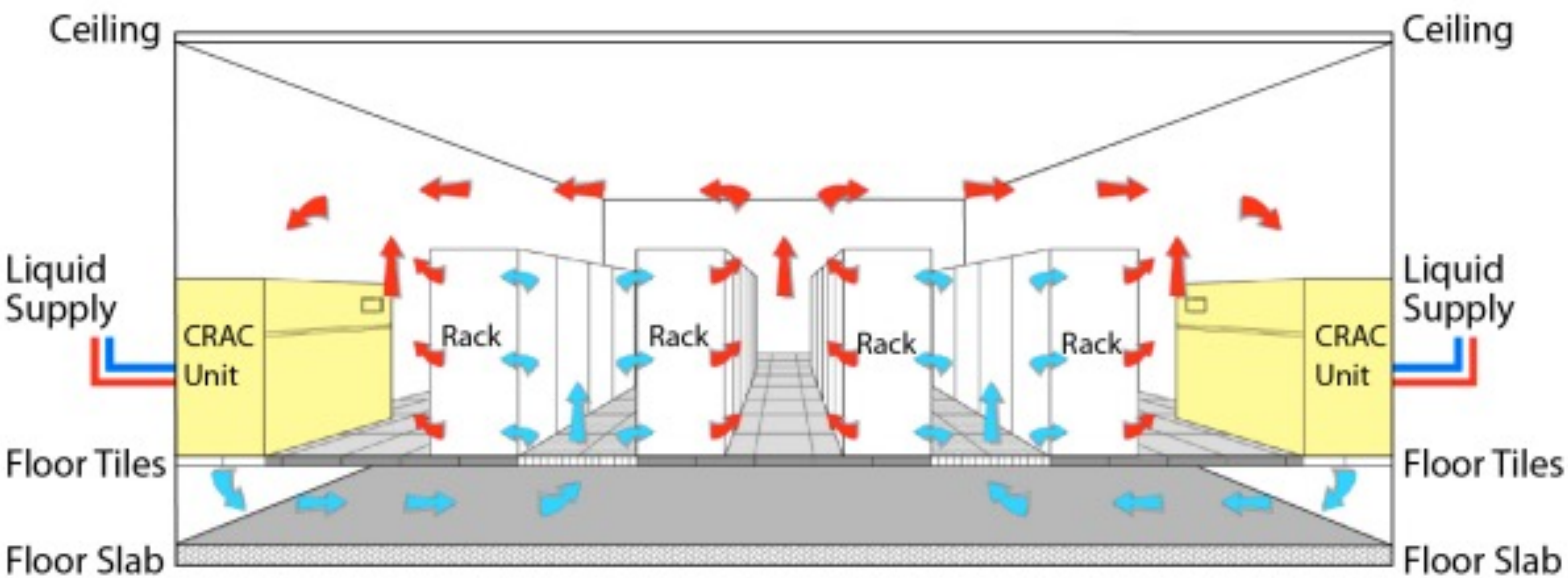
Anatomy of a Datacenter



Source: Barroso and Urs Hölzle (2013)

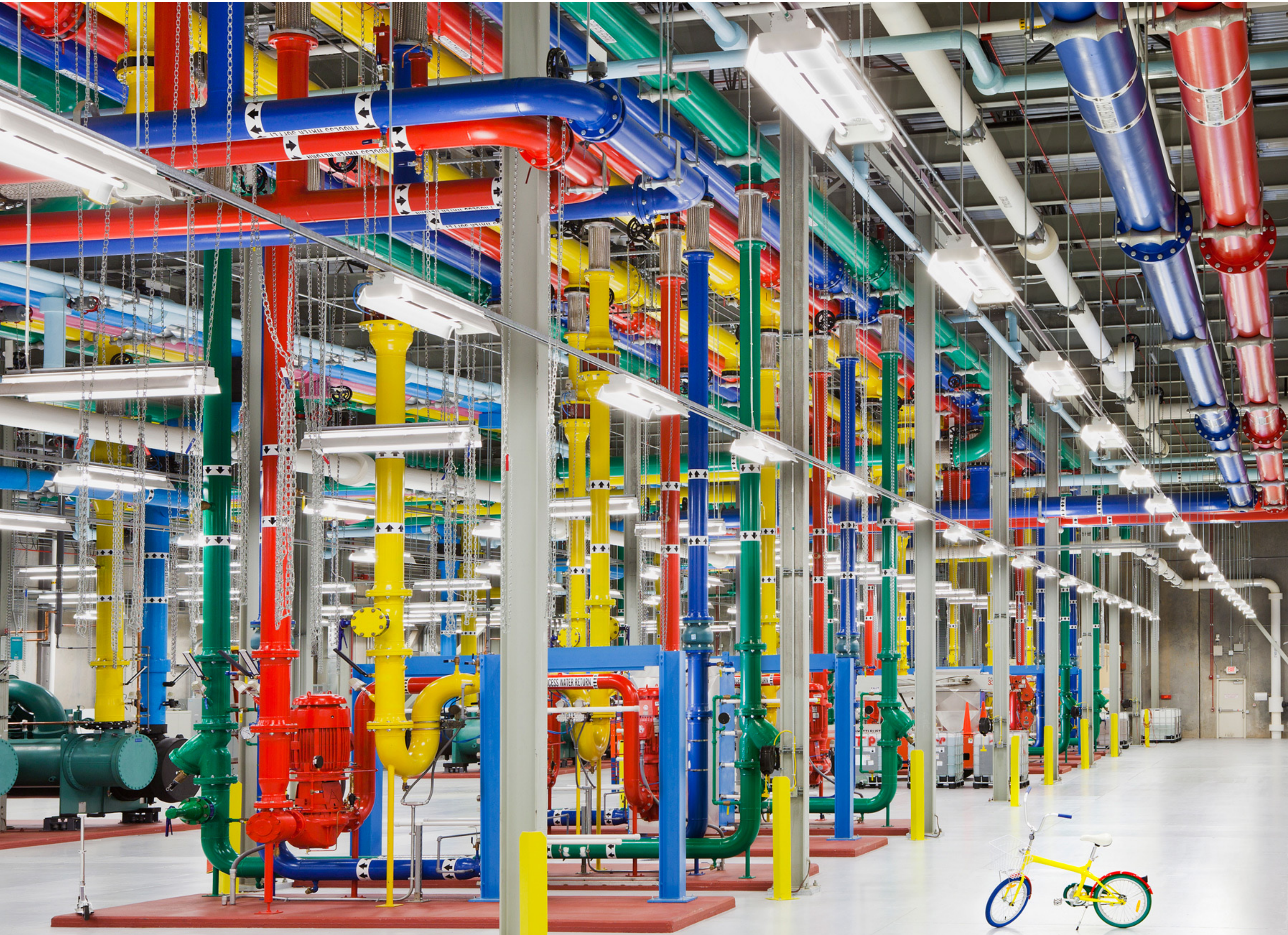
Datacenter Cooling

What's a computer?



Source: Barroso and Urs Hölzle (2013)

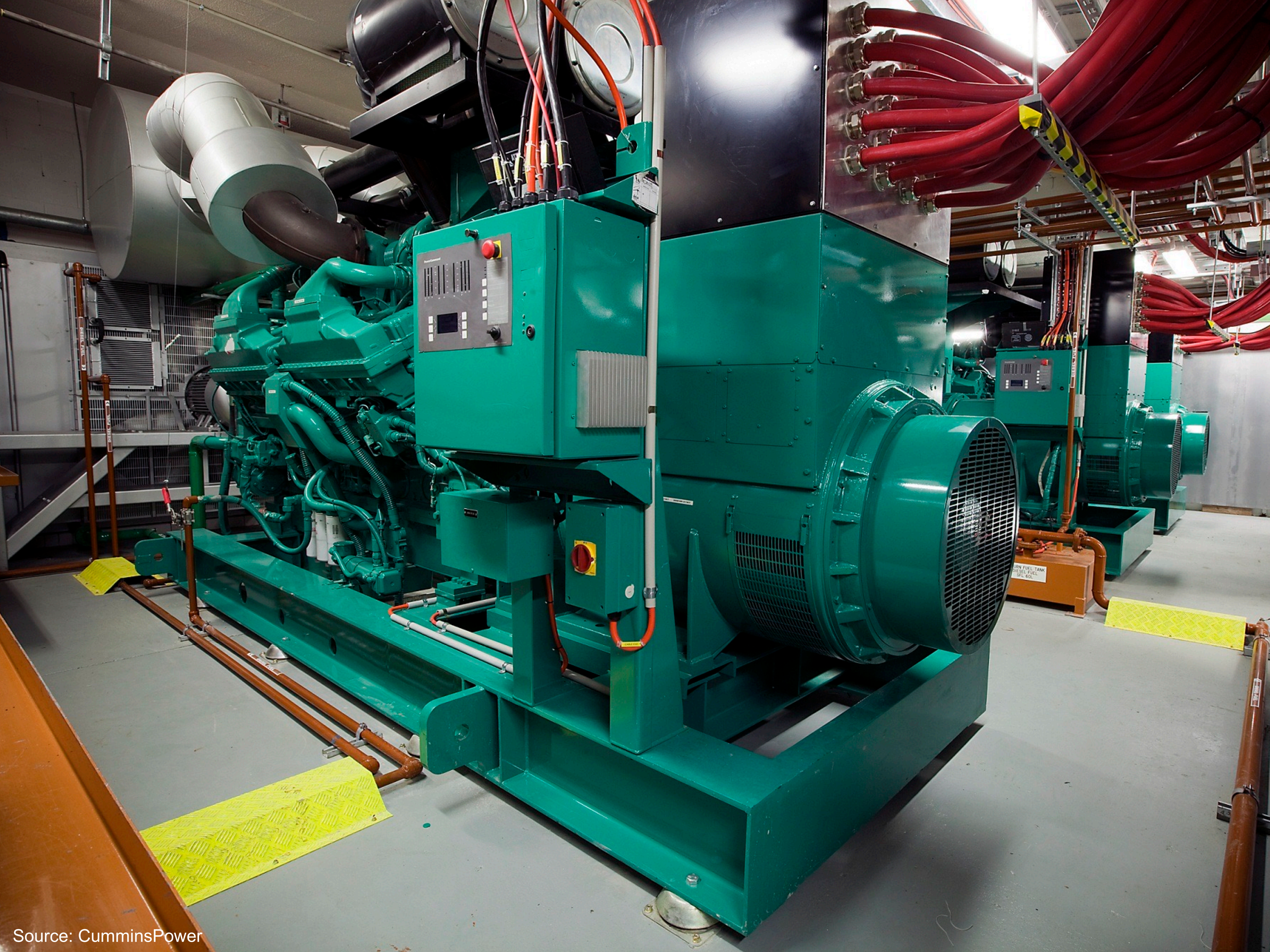
Source: Google



Source: Google


Source: Google

Source: Google

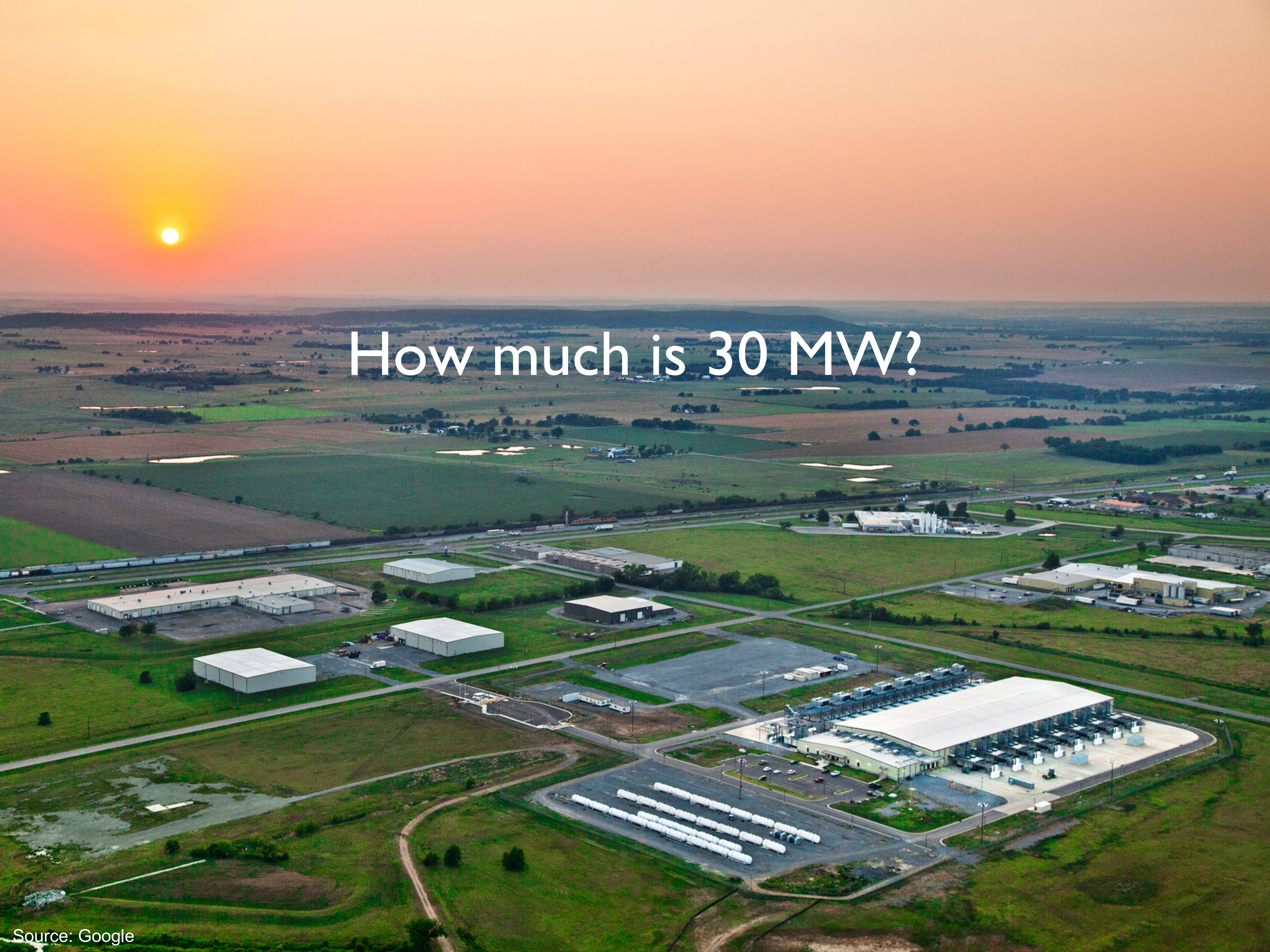


Source: CumminsPower


Source: Google


Source: Wikipedia (The Dalles, Oregon)

Source: Bonneville Power Administration

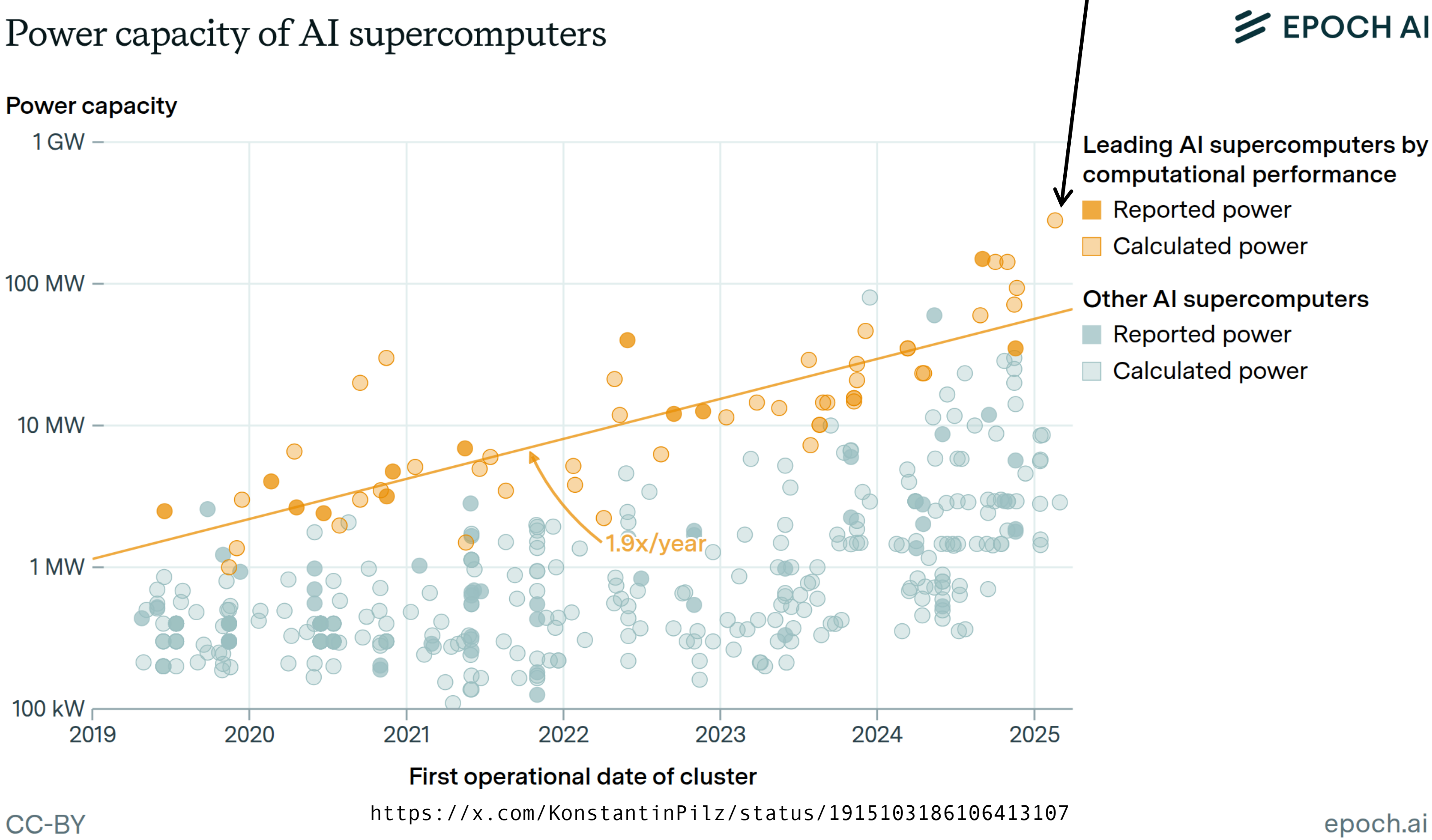

How much is 30 MW?
Source: Google

Konstantin Pilz
@KonstantinPilz

After 2 years tracking GPU clusters, we're releasing our dataset of 700+ AI supercomputers.

The US clearly dominates countries, and xAI's Colossus is leading system: 200k AI chips, $7B price tag, and power needs of a medium-sized city.
Here are my personal highlights🧵

Name	xAI Colossus Memphis Phase 2
First operational date	Feb. 18, 2025
Hardware	150,000 NVIDIA H100 SXM5 80GB
Secondary hardware	50,000 NVIDIA H200 SXM
H100 equivalents (8-bit)	200,000
Power capacity	280 MW
Country	United States of America



https://x.com/KonstantinPilz/status/1915103186106413107

Elon Musk @elonmusk

Subscribe ···

Colossus 2, built by @xAI, will be the world's first Gigawatt+ AI training supercomputer

> **Michael Dell** 🇺🇸 @MichaelDell · Aug 21
>
> Great visit to @xai with @BrentM_SpaceX @nmswede today! It's amazing to see what you guys are accomplishing and we couldn't be prouder to be part of it. I very much enjoyed it. Onward 🚀 x.com/BrentM_SpaceX/...

7:01 AM · Aug 22, 2025 · **25M** Views

https://x.com/elonmusk/status/1958846872157921546


Sir Adam Beck Hydroelectric
Generating Stations: 1,962 MW
Source: Wikipedia

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

Example: SSD Failure

Thanks to ChatGPT 😅

Assume AFR (Annual Failure Rate) of 1% (= 0.01 per year)
Assume constant hazard

The per-day failure probability for one drive is:
$p_{day} = 0.01/365 \approx 0.000027397$

For N independent drives, the daily failure count is well-approximated by a Poisson random variable with rate: $\lambda = N \times p_{day}$

Expected failures per day = λ
Chance of at least one failure today = $1 - e^{-\lambda}$

10,000 SSDs: ≈ 0.274 failures / day
$P(\geq 1$ failure today$) \approx 24\%$

100,000 SSDs: ≈ 2.74 failures / day
$P(\geq$ failure today$) \approx 94\%$

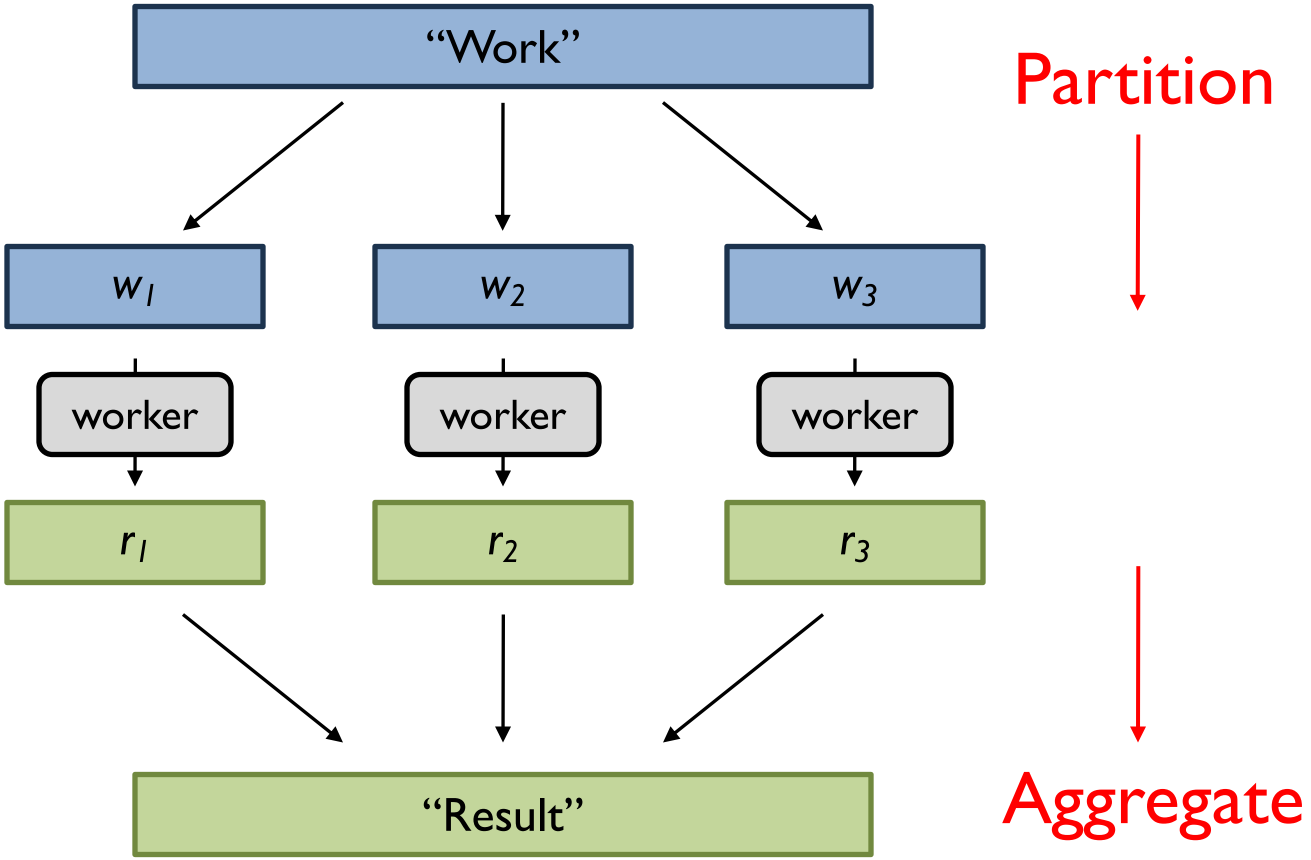
https://www.backblaze.com/blog/ssd-edition-2023-mid-year-drive-stats-review/

Data-Intensive Distributed Processing

Divide and Conquer!


THIS IS THE WAY

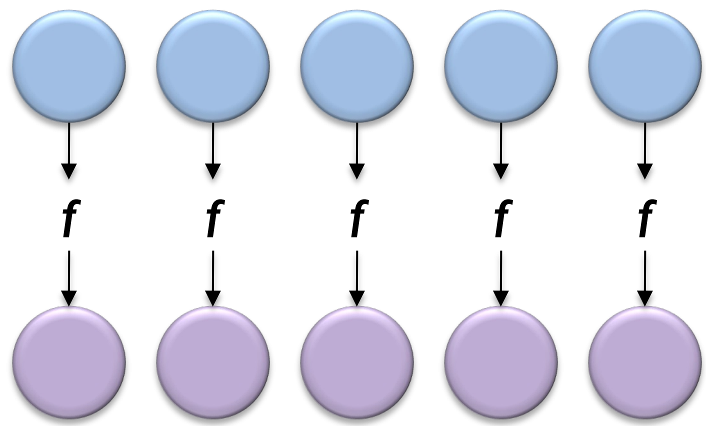
Divide and Conquer



Roots in Functional Programming

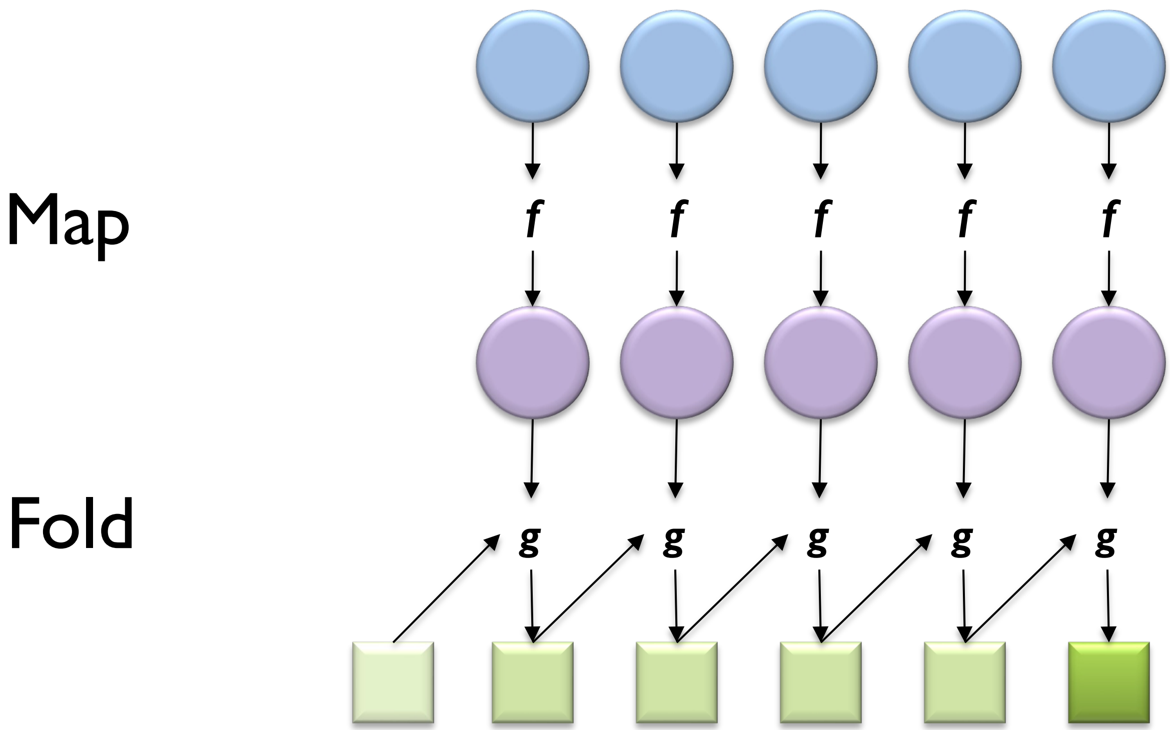
Partition: process many records by "doing" something to each (*f*)

Map



Roots in Functional Programming

Aggregate: combine results in a particular way (g)



Functional Programming in Scala

```
scala> val t = Array(1, 2, 3, 4, 5)
t: Array[Int] = Array(1, 2, 3, 4, 5)

scala> t.map(n => n*n)
res0: Array[Int] = Array(1, 4, 9, 16, 25)

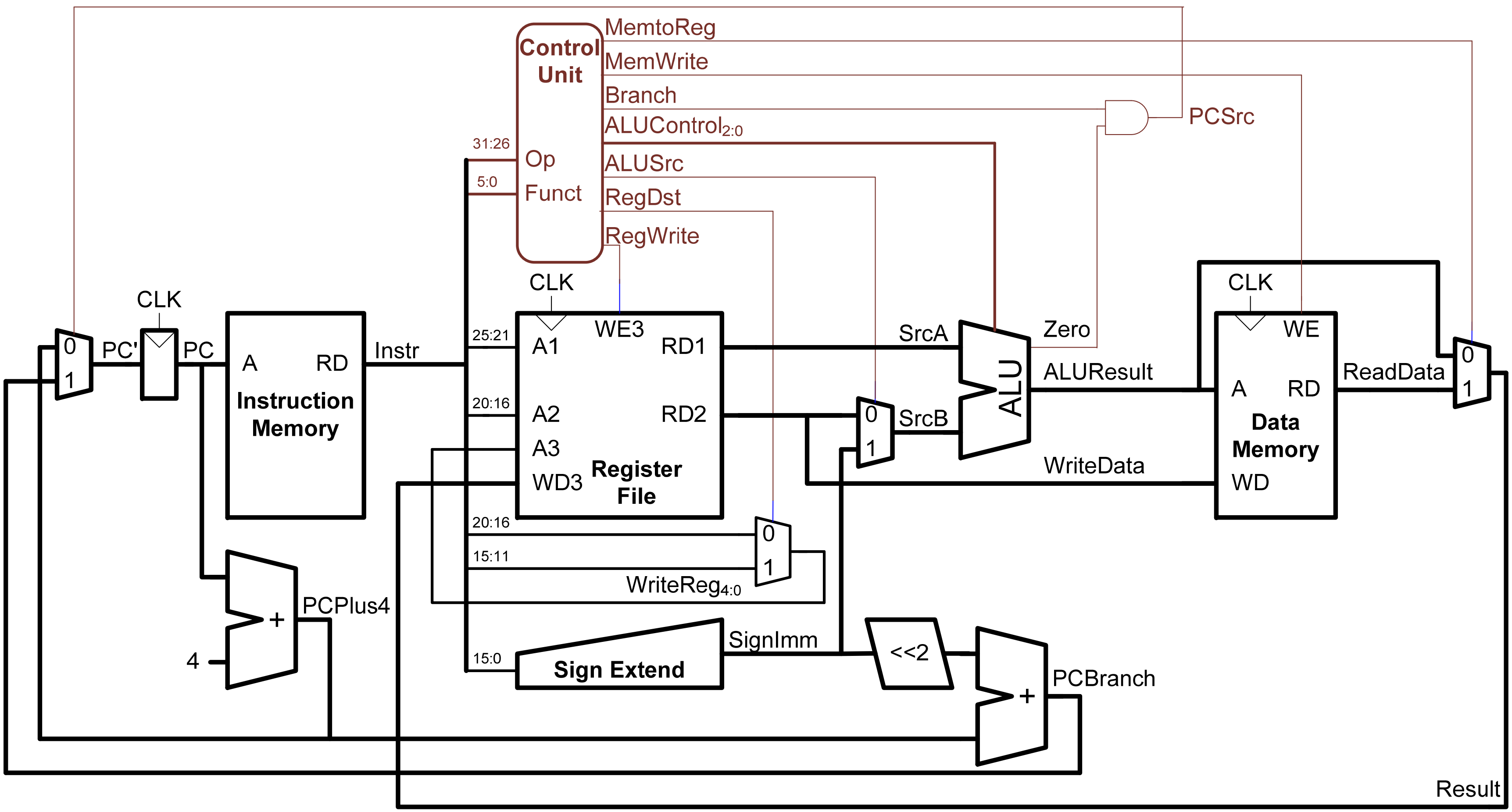
scala> t.map(n => n*n).foldLeft(0)((m, n) => m + n)
res1: Int = 55
```

Now do this across many machines…

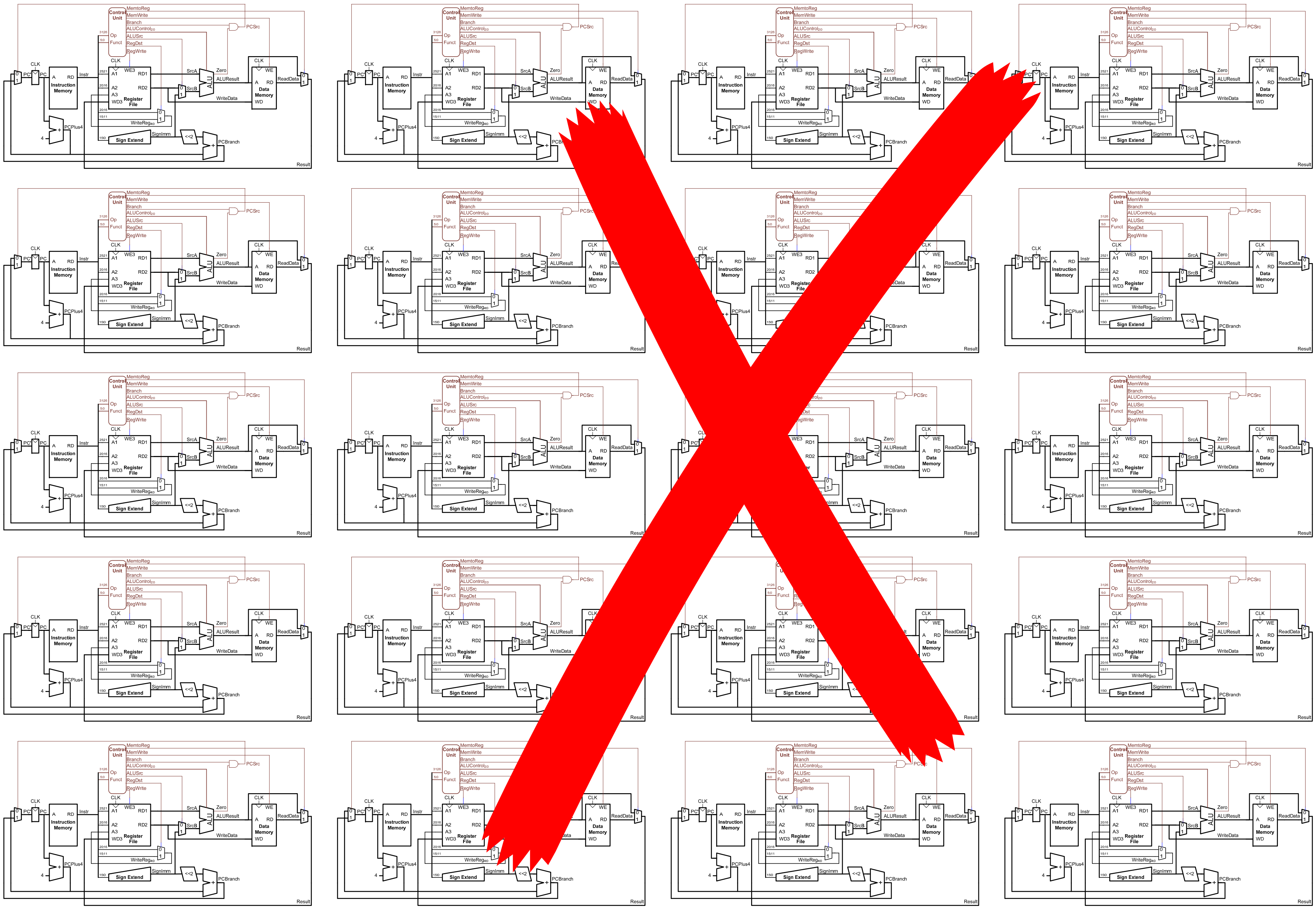
Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

How do you write a program that runs across 100 machines?



Source: CS 251



Source: CS 251

Source: Google


The datacenter *is* the computer!
Source: Google

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

How do you write a program that runs across 100 machines?

Implications

Must build higher-level abstractions

Must think about fault tolerance from the beginning

The essence of abstraction is preserving information that is relevant in a given context, and forgetting information that is irrelevant in that context.

– computer scientist John V. Guttag


The datacenter *is* the computer!
Source: Google

The datacenter *is* the computer!

What's the instruction set?

Source: Google

A Data-Parallel Abstraction

Start with a large number of records

Map "Do something" to each

Group intermediate results

"Aggregate" intermediate results

Reduce

Write final results

Key idea: provide a functional abstraction for these two operations

Dean and Ghemawat (2004)

Historical Note

Google “invented” MapReduce

Hadoop is an open-source implementation

Unless explicitly stated otherwise, we’re referring to Hadoop

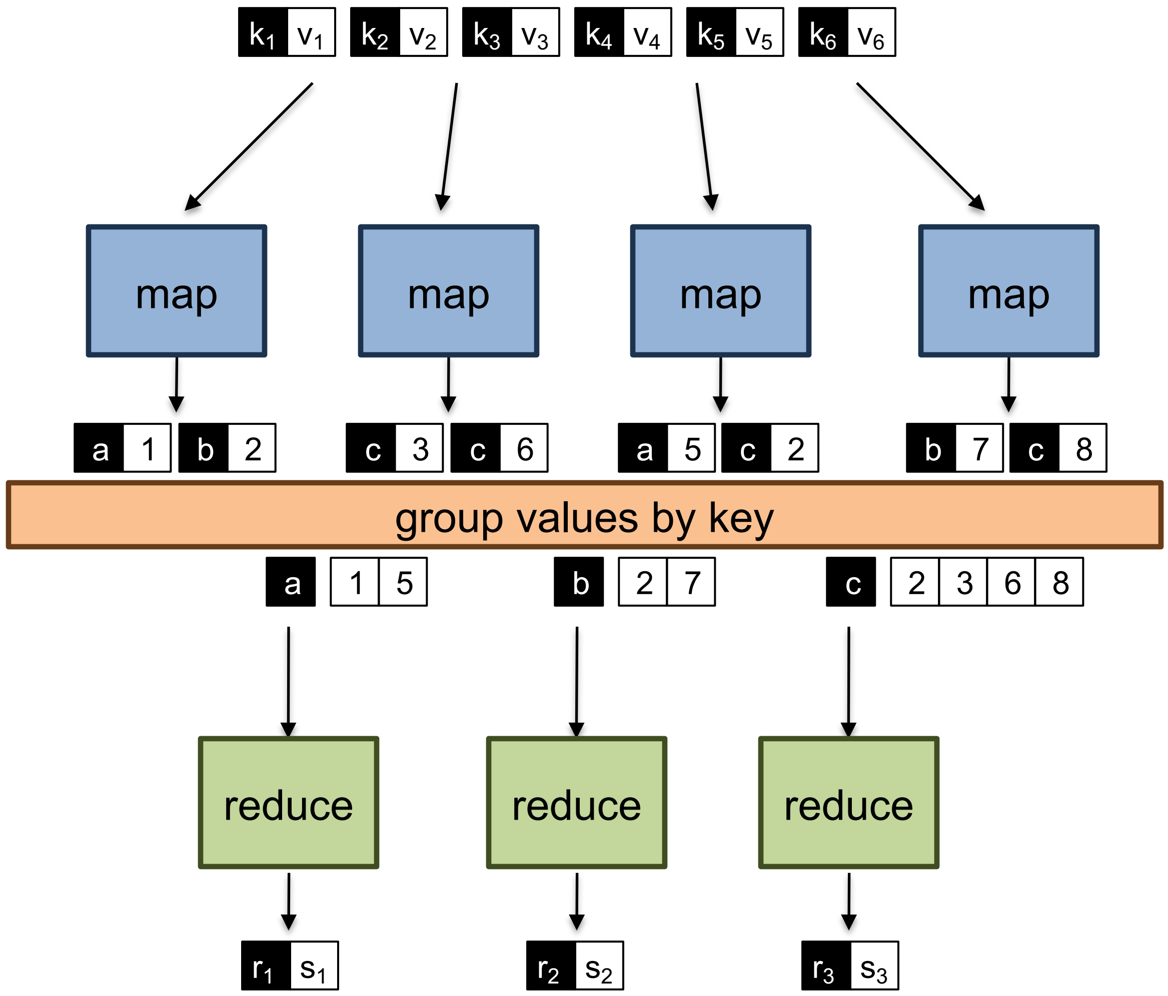
MapReduce

Programmer specifies two functions:

$$\texttt{map}\ (k_1,\ v_1) \rightarrow \text{List}[(k_2,\ v_2)]$$

$$\texttt{reduce}\ (k_2,\ \text{List}[v_2]) \rightarrow \text{List}[(k_3,\ v_3)]$$

All values with the same key are sent to the same reducer



k_1 v_1 k_2 v_2 k_3 v_3 k_4 v_4 k_5 v_5 k_6 v_6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
group values by key
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r_1 s_1
r_2 s_2
r_3 s_3

MapReduce

Programmer specifies two functions:

$\texttt{map}\ (k_1,\ v_1) \rightarrow \text{List}[(k_2,\ v_2)]$

$\texttt{reduce}\ (k_2,\ \text{List}[v_2]) \rightarrow \text{List}[(k_3,\ v_3)]$

All values with the same key are sent to the same reducer

The “runtime” handles everything else…

What’s “everything else”?

MapReduce “Runtime”

Handles scheduling

Assigns workers to map and reduce tasks

Handles “data distribution”

Moves code to data

Handles coordination

Groups and shuffles intermediate data

Handles errors and faults

Detects failures and compensates

MapReduce

Programmer specifies two functions:

$\texttt{map}\ (k_1, v_1) \rightarrow \texttt{List}[(k_2, v_2)]$

$\texttt{reduce}\ (k_2, \texttt{List}[v_2]) \rightarrow \texttt{List}[(k_3, v_3)]$

All values with the same key are sent to the same reducer

The "runtime" handles everything else…

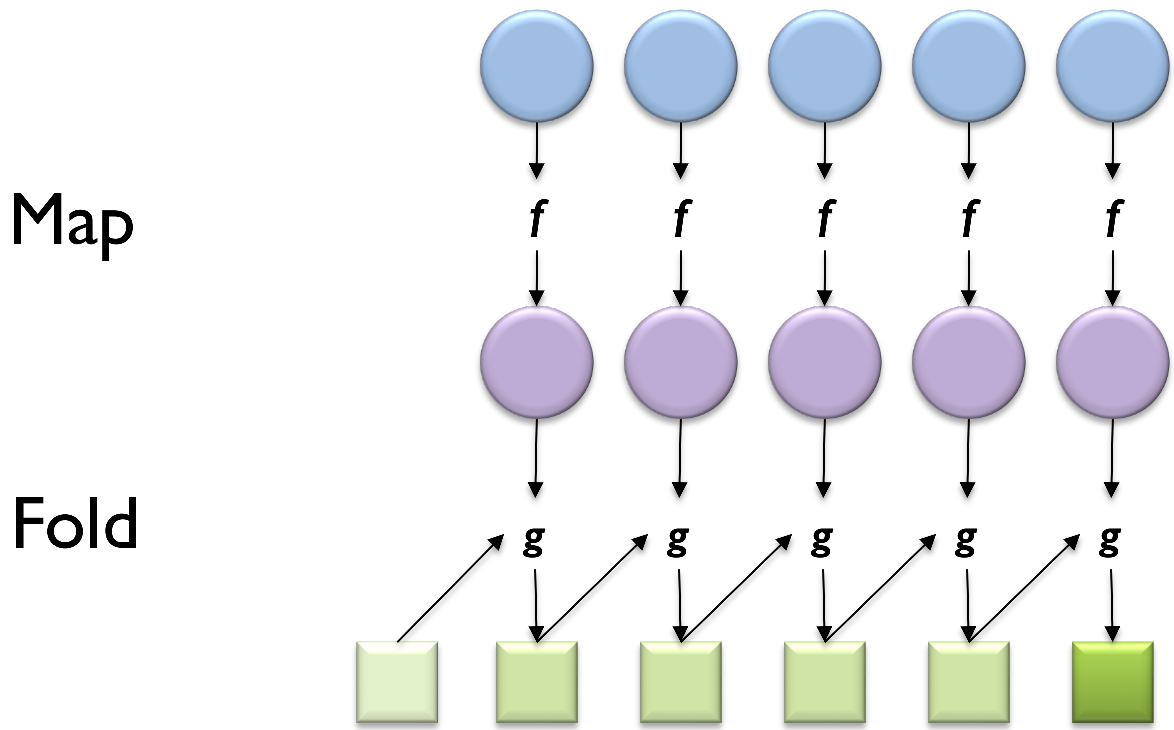
(Not quite… but later)

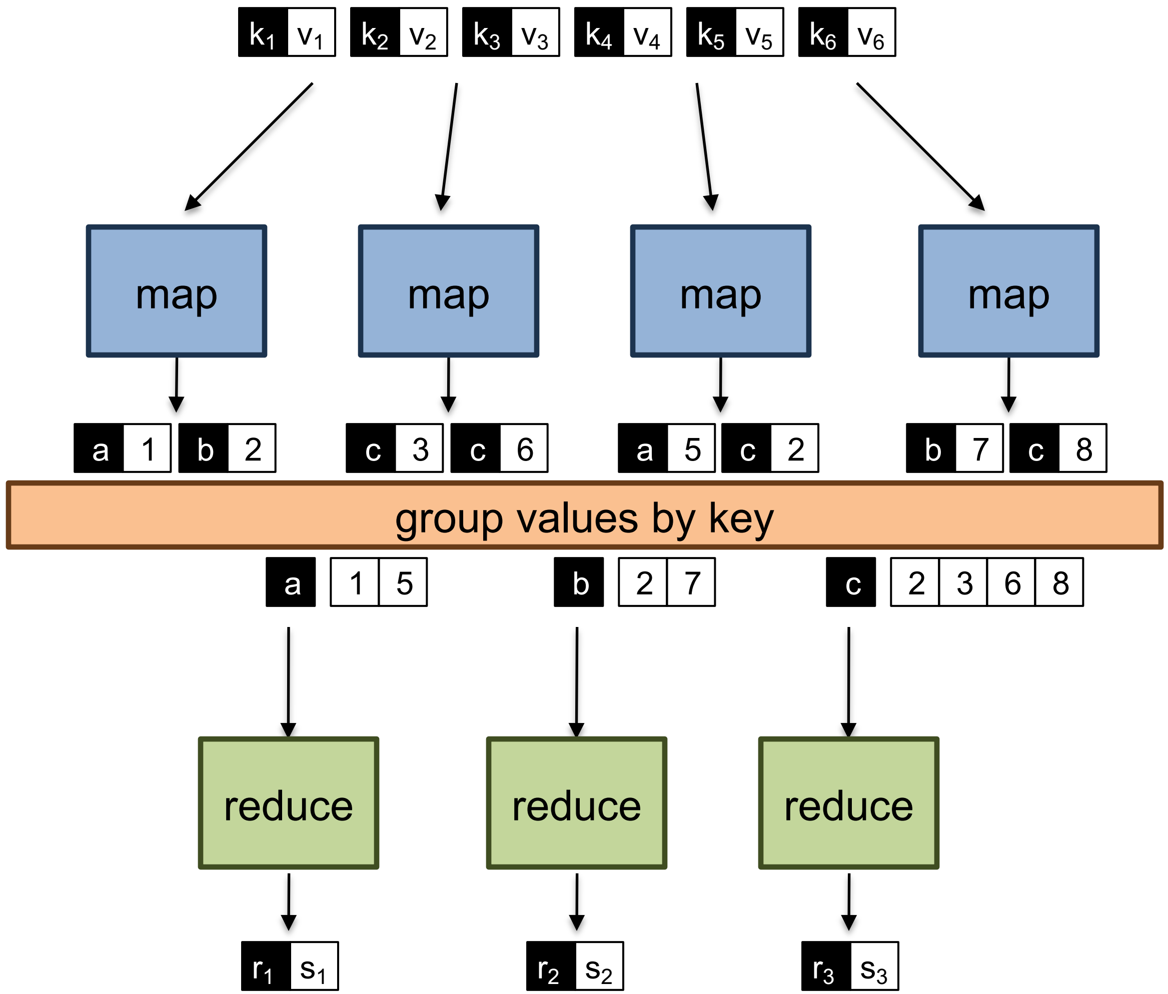
“Hello World” MapReduce: Word Count

```
def map(key: Long, value: String) = {
  for (word <- tokenize(value)) {
    emit(word, 1)
  }
}


def reduce(key: String, values: Iterable[Int]) = {
  for (value <- values) {
    sum += value
  }
  emit(key, sum)
}
```

Roots in Functional Programming




k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
map
map
map
a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
group values by key
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

That's it.

MapReduce

```
results = records.map(...)
                 .reduce(...)

results2 = results1.map(...)
                   .reduce(...)
```

Spark

```
results = rdd.foo(...)
             .bar(...)
             .baz(...)
```

More? Why do you care?

The essence of abstraction is preserving information that is relevant in a given context, and forgetting information that is irrelevant in that context.

– computer scientist John V. Guttag

1. All abstractions are *leaky*
2. Important to develop intuitions
3. What do you want to be?
4. Curiosity

You don't have to be an engineer to be be a racing driver,
but you do have to have mechanical sympathy

– Formula One driver Jackie Stewart

One More…

In the cloud, does any of this matter?

The cloud is just another abstraction!

Pros

You don’t have to worry about it.
You don’t need to know what’s going on.

Cons

You can’t worry about it (even if you wanted to).
You don’t know what’s going on (even if you wanted to).

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

Trick #1: Partition

Trick #2: Replicate

Remember: There are no solutions, only tradeoffs!

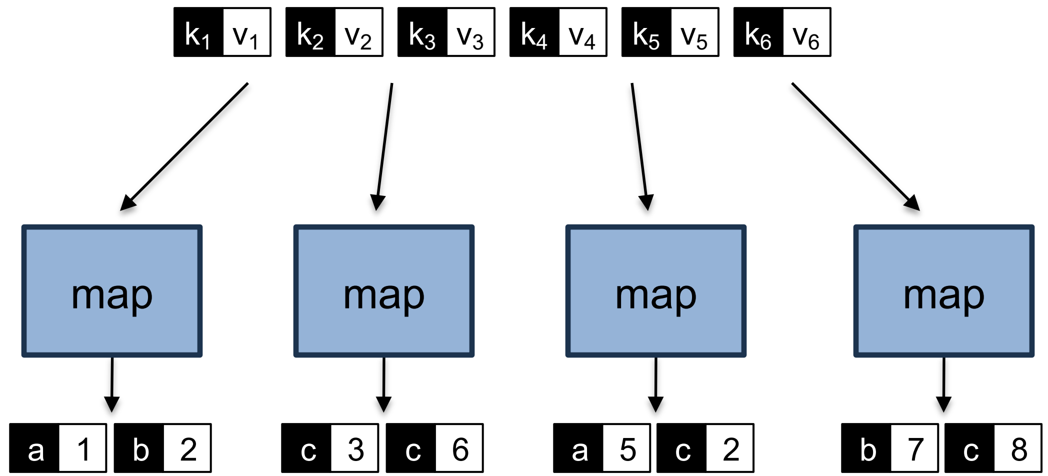
Partition

tl;dr – (1) divide data and store across multiple machines;
(2) divide processing across multiple machine

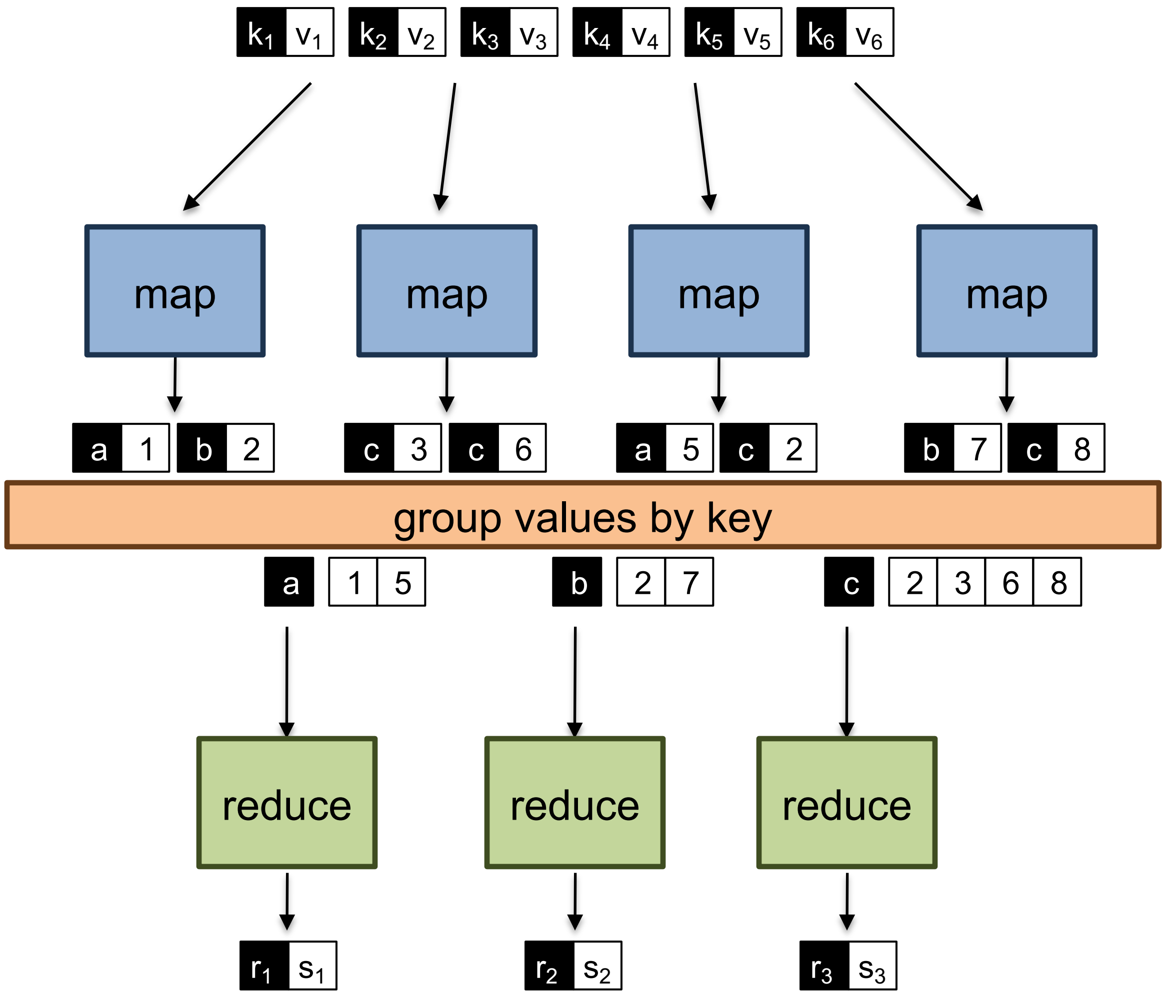
Challenges

How do we divide data?
Where do we place data? (mapping data to machines)
Where do we place workers? (mapping workers to machines)
How do workers access data? (mapping data to workers)

(Who's "we", btw?)



Okay, now what?



k1 v1 k2 v2 k3 v3 k4 v4 k5 v5 k6 v6
map
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map
map
a 1 b 2
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b 7 c 8
group values by key
a 1 5
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c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

Partition

tl;dr – (1) divide data and store across multiple machines;
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Challenges

How do we divide data?
Where do we place data? (mapping data to machines)
Where do we place workers? (mapping workers to machines)
How do workers access data? (mapping data to workers)

How do we share intermediate results?

Replicate

tl;dr – keep multiple copies for fault tolerance

Challenges

How many copies do we keep?
Where do we keep them?
How do we keep all the copies in sync?
Which copy do we process?

(caching as a special case)

Orchestration

tl;dr – we need to coordinate *all of this*

Challenges

How do we do *all of this* in the presence of unreliable components?
How do we do *all of this* keeping every machine busy?

When workers die? *unpredictable*
When workers finish? *unpredictable*
When workers interrupt each other? *unpredictable*
When workers access resources? *unpredictable*

CAP Theorem

Consistency
Availability
Partition Tolerance

Choose two!

In practical terms, if we have a network partition (P):
What do we do?

Choose A (AP system)
What happens to C?

Choose C (CP system)
What happens to A?

Data-Intensive Distributed Processing

How do you *actually* do it?

Hadoop provides *one* answer…

Immutable Truth #1: At scale, you must distribute work across multiple machines.

Immutable Truth #2: At scale, computing components break all the time.

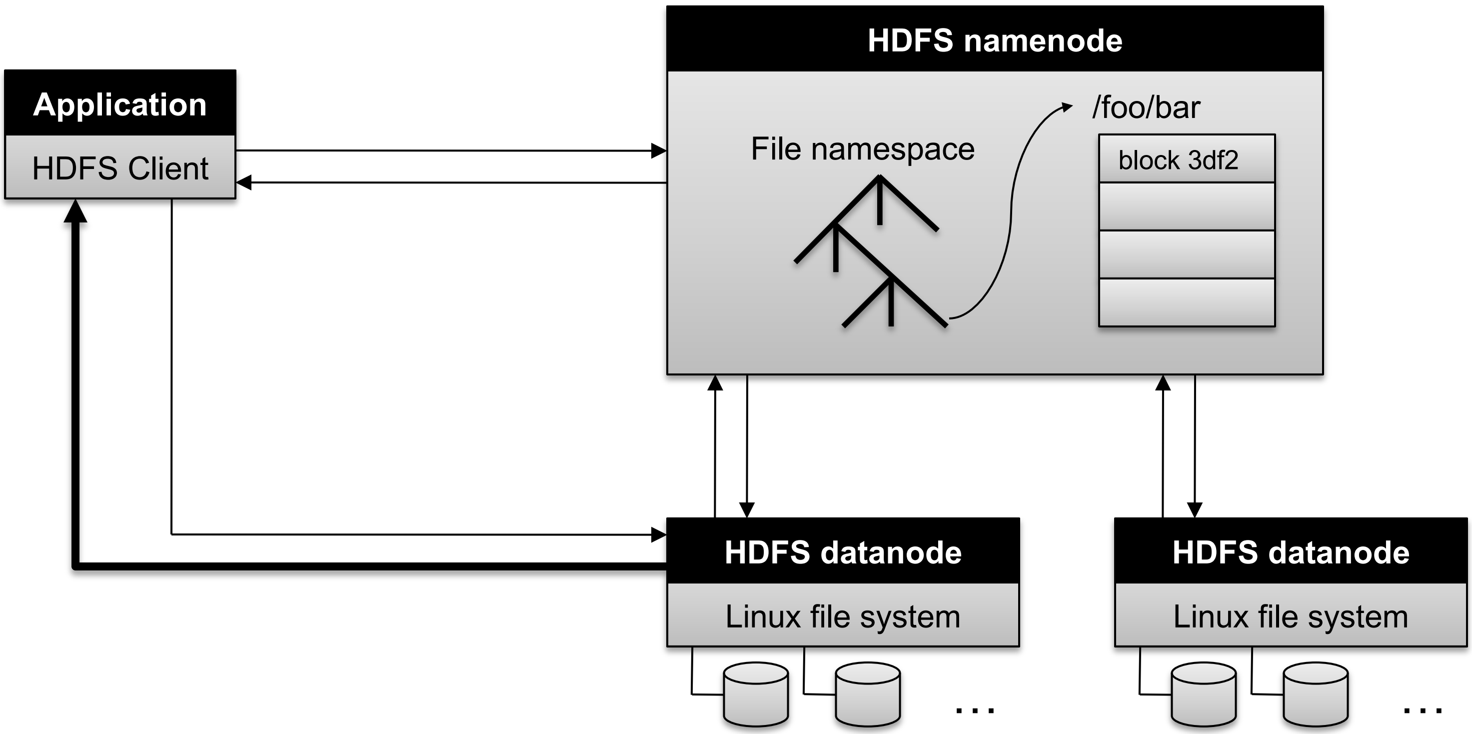
Where do we place the data?

Trick #1: Partition

Trick #2: Replicate

Remember: There are no solutions, only tradeoffs!

HDFS Architecture



Adapted from (Ghemawat et al., SOSP 2003)

Immutable Truth #1: At scale, you must distribute work across multiple machines.

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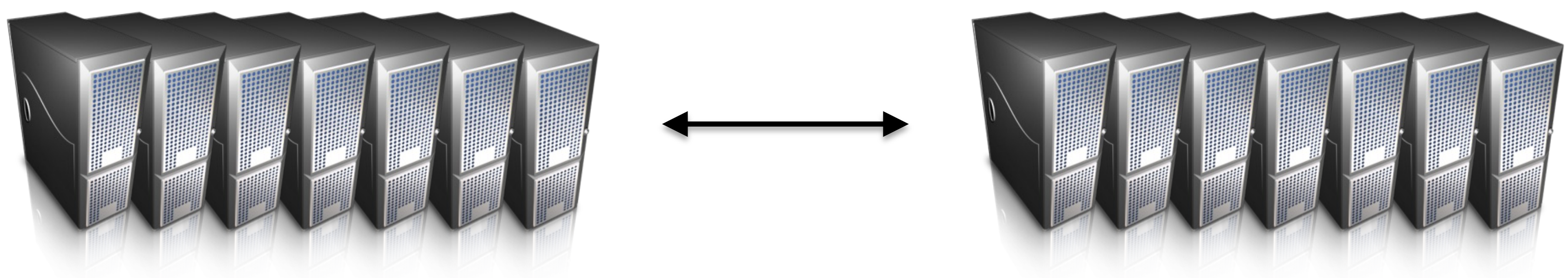
Where do we place the compute?

Trick #1: Partition

Trick #2: Replicate

Remember: There are no solutions, only tradeoffs!

Compute meets Data!



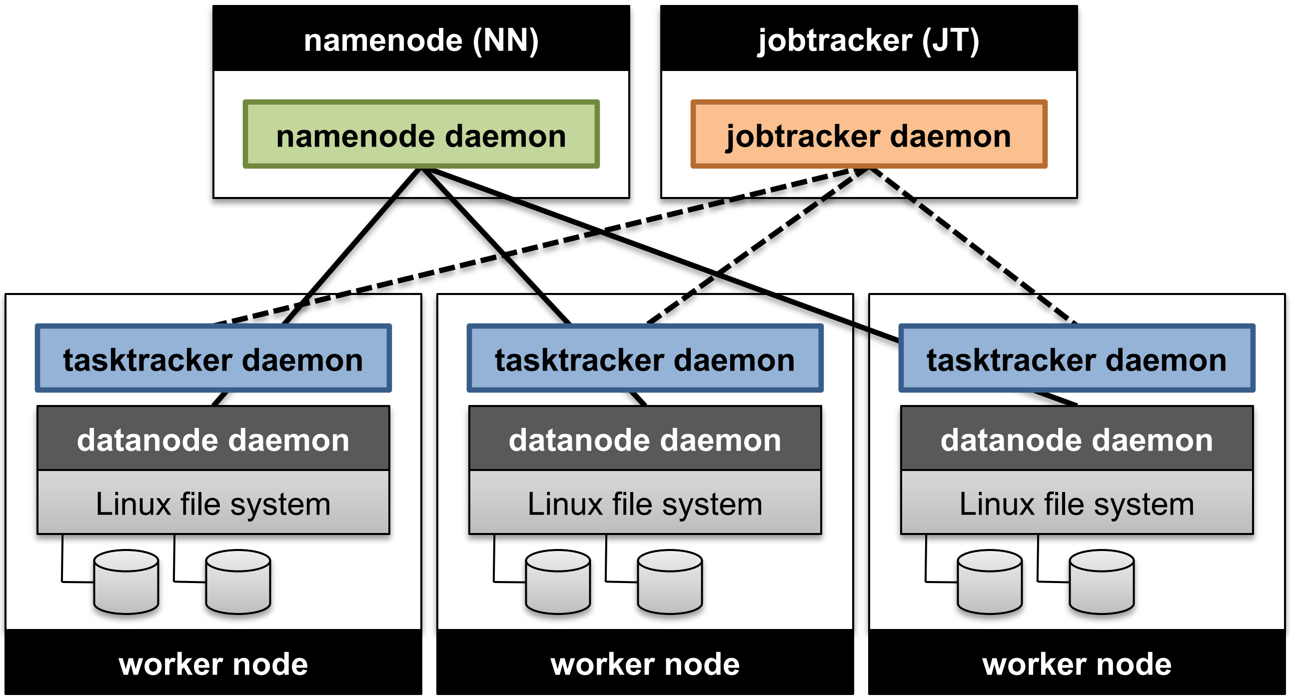
Compute Nodes

Storage Nodes

Move data to compute?

Move compute to data?

Putting everything together…



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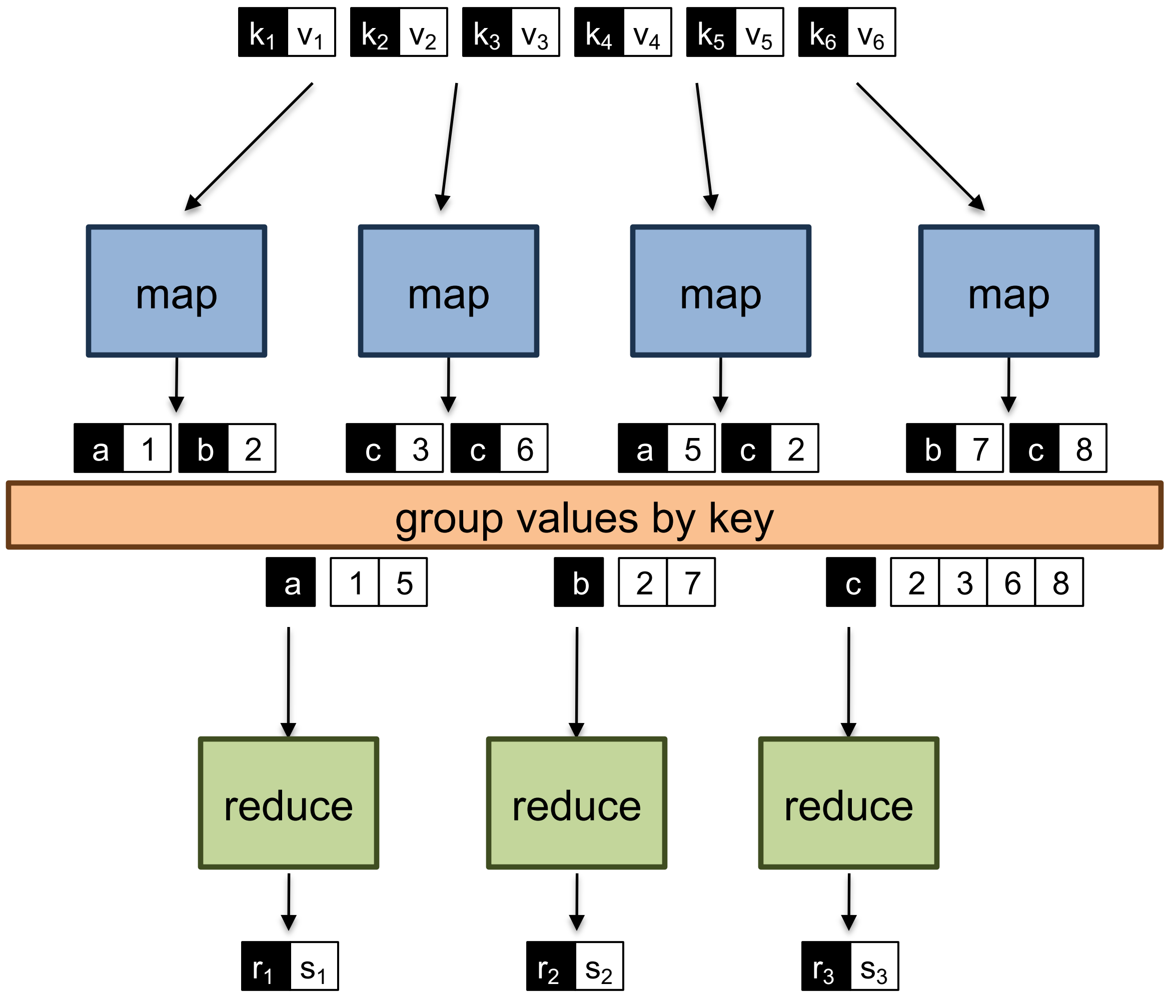
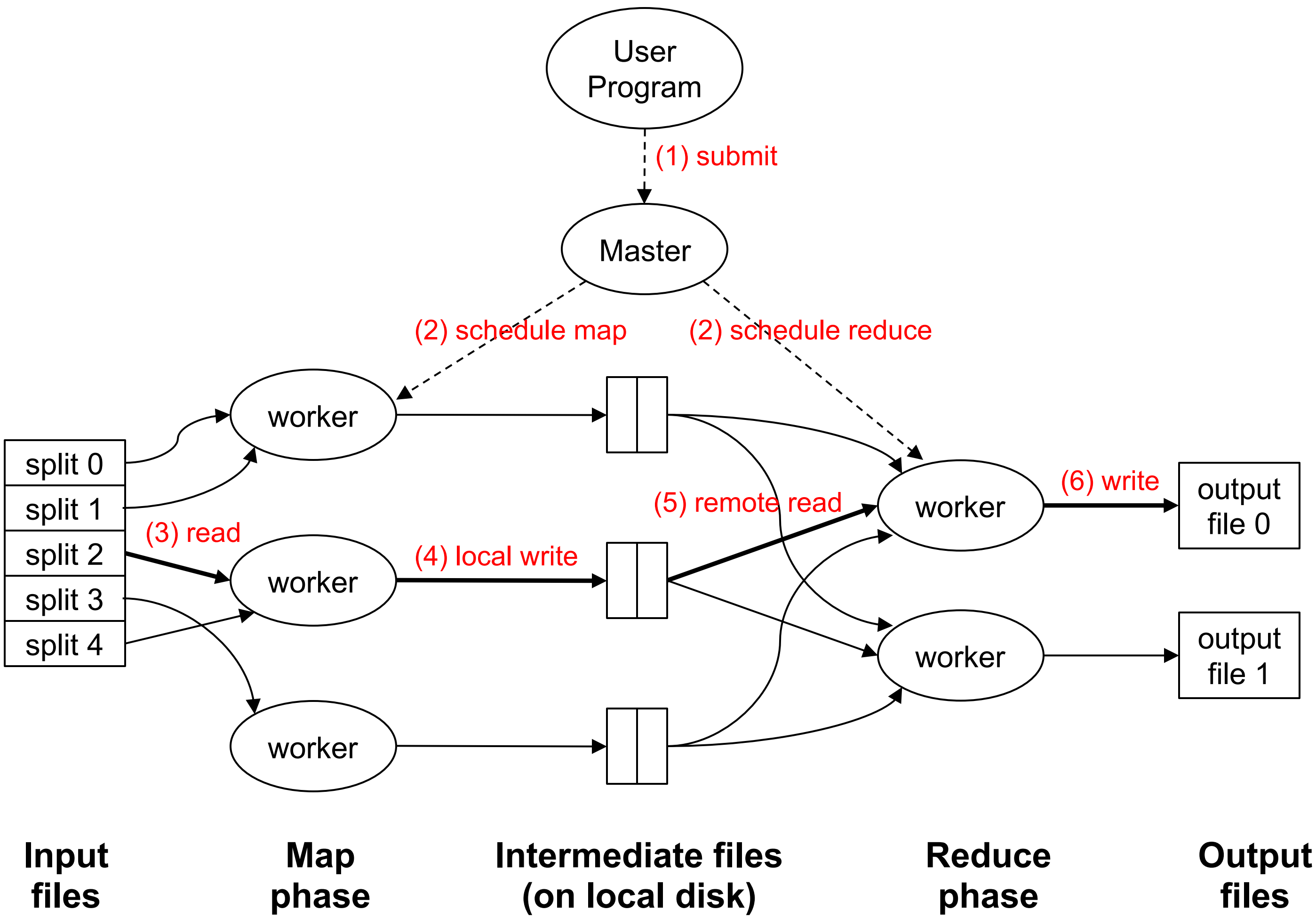
}
```

Logical View



Physical View



Adapted from (Dean and Ghemawat, OSDI 2004)


EXPRESSWAY
TOYOTA
COROLLA LE
ONTARIO
HADOOP
YOURS TO DISCOVER