



# MapReduce and Concurrency in Go

CS 675: *Distributed Systems* (Spring 2020)

Lecture 3

Yue Cheng

Some material taken/derived from:

- Princeton COS-418 materials created by Michael Freedman and Wyatt Lloyd.
- MIT 6.824 by Robert Morris, Frans Kaashoek, and Nickolai Zeldovich.
- Utah CS6450 by Ryan Stutsman.
- Wisconsin CS744 by Shivaram Venkataraman.

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## Applications

Web  
apps

Data  
processing

Data  
storage

Emerging  
apps?

## Resource management

Compute  
resources

Memory  
resources

Storage  
resources

Network  
resources



## Datacenter infrastructure



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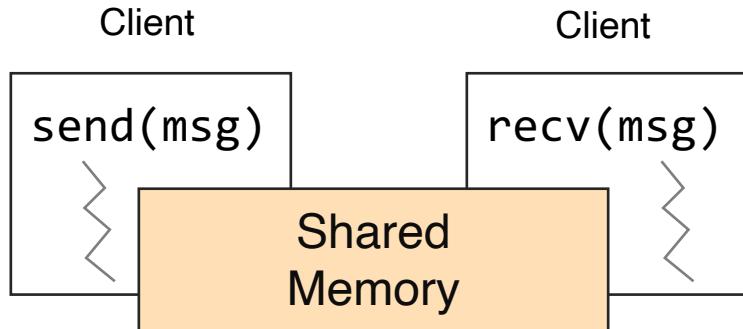
**Question:** How to program these many computers?



Datacenter architecture

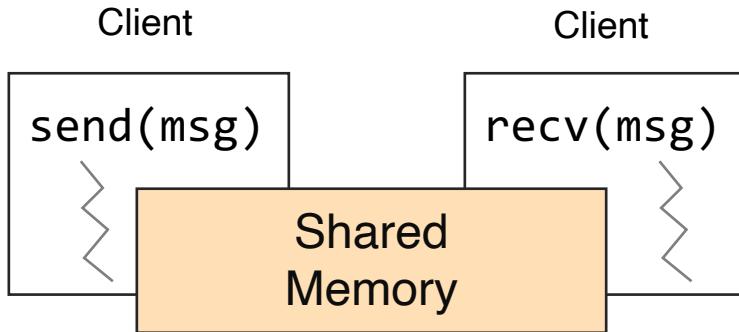


# Shared memory

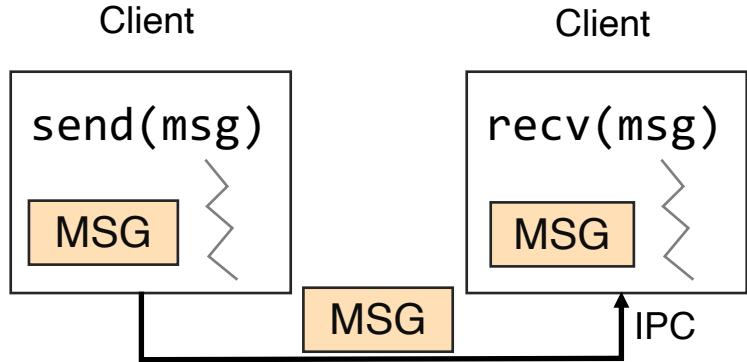


- Shared memory: all multiple processes to share data via memory
- Applications must locate and map shared memory regions to exchange data

# Shared memory vs. Message passing



- Shared memory: all multiple processes share data via memory
- Applications must locate and map shared memory regions to exchange data



- Message passing: exchange data explicitly via IPC
- Application developers define protocol and exchanging format, number of participants, and each exchange

# Shared memory vs. Message passing

# Shared memory vs. Message passing

- Easy to program; just like a single multi-threaded machines
- Hard to write high perf. apps:
  - Cannot control which data is local or remote (remote mem. access much slower)
- Hard to mask failures
- Message passing: can write very high perf. apps
- Hard to write apps:
  - Need to manually decompose the app, and move data
  - Need to manually handle failures

# Background: Pthread

- A POSIX standard (IEEE 1003.1c) API for thread creation and synchronization
- API specifies behavior of the thread library, implementation is up to development of the library
- Common in UNIX (e.g., Linux) OSes

# Background: Pthread

```
void *myThreadFun(void *vargp) {
    sleep(1);
    printf("Hello world\n");
    return NULL;
}

int main() {
    pthread_t thread_id_1, thread_id_2;
    pthread_create(&thread_id_1, NULL, myThreadFun, NULL);
    pthread_create(&thread_id_2, NULL, myThreadFun, NULL);
    pthread_join(thread_id_1, NULL);
    pthread_join(thread_id_2, NULL);
    exit(0);
}
```

# Background: MPI

- MPI – Message Passing Interface
  - Library standard defined by a committee of vendors, implementers, and parallel programmers
  - Used to create parallel programs based on message passing
- Portable: one standard, many implementations
  - Available on almost all parallel machines in C and Fortran
  - De facto standard platform for the HPC community

# Background: MPI

```
int main(int argc, char **argv) {
    MPI_Init(NULL, NULL);

    // Get the number of processes
    int world_size;
    MPI_Comm_size(MPI_COMM_WORLD, &world_size);

    // Get the rank of the process
    int world_rank;
    MPI_Comm_rank(MPI_COMM_WORLD, *world_rank);

    // Print off a hello world message
    printf("Hello world from rank %d out of %d processors\n",
           world_rank, world_size);

    // Finalize the MPI environment
    MPI_Finalize();
}
```

# Background: MPI

```
mpirun -n 4 -f host_file ./mpi_hello_world
```

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# Today's outline

1. Google MapReduce
2. Concurrency in Go

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- Datasets are **too big** to process using a single computer
- Good parallel processing engines are **rare** (back then in the late 90s)
- Want a parallel processing framework that:
  - is **general** (works for many problems)
  - is **easy to use** (no locks, no need to explicitly handle communication, no race conditions)
  - can **automatically parallelize** tasks
  - can **automatically handle** machine failures

# Context (Google circa 2000)

- Starting to deal with **massive** datasets
- But also addicted to cheap, unreliable hardware
  - Young company, expensive hardware not practical
- Only a few expert programmers can write distributed programs to process them
  - Scale so large jobs can complete before failures

# Context (Google circa 2000)

- Starting to deal with **massive** datasets
- But also addicted to cheap, unreliable hardware
  - Young company, expensive hardware not practical
- Only a few expert programmers can write distributed programs to process them
  - Scale so large jobs can complete before failures
- **Key question:** how can every Google engineer be imbued with the ability to write **parallel**, **scalable**, **distributed**, **fault-tolerant** code?
- **Solution:** **abstract out** the redundant parts
- **Restriction:** relies on job semantics, so restricts which problems it works for

# Application: Word Count

```
cat data.txt  
| tr -s '[:punct:][:space:]' '\n'  
| sort | uniq -c
```

```
SELECT count(word), word FROM data  
GROUP BY word
```

# Deal with multiple files?

1. Compute word counts from individual files

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# MapReduce: Programming interface

- $\text{map}(\text{k1}, \text{v1}) \rightarrow \text{list}(\text{k2}, \text{v2})$ 
  - Apply function to  $(\text{k1}, \text{v1})$  pair and produce set of intermediate pairs  $(\text{k2}, \text{v2})$
- $\text{reduce}(\text{k2}, \text{list}(\text{v2})) \rightarrow \text{list}(\text{k3}, \text{v3})$ 
  - Apply aggregation (reduce) function to values
  - Output results

# MapReduce: Word Count

```
map(key, value):
```

```
    for each word w in value:
```

```
        EmitIntermediate(w, "1");
```

```
reduce(key, values):
```

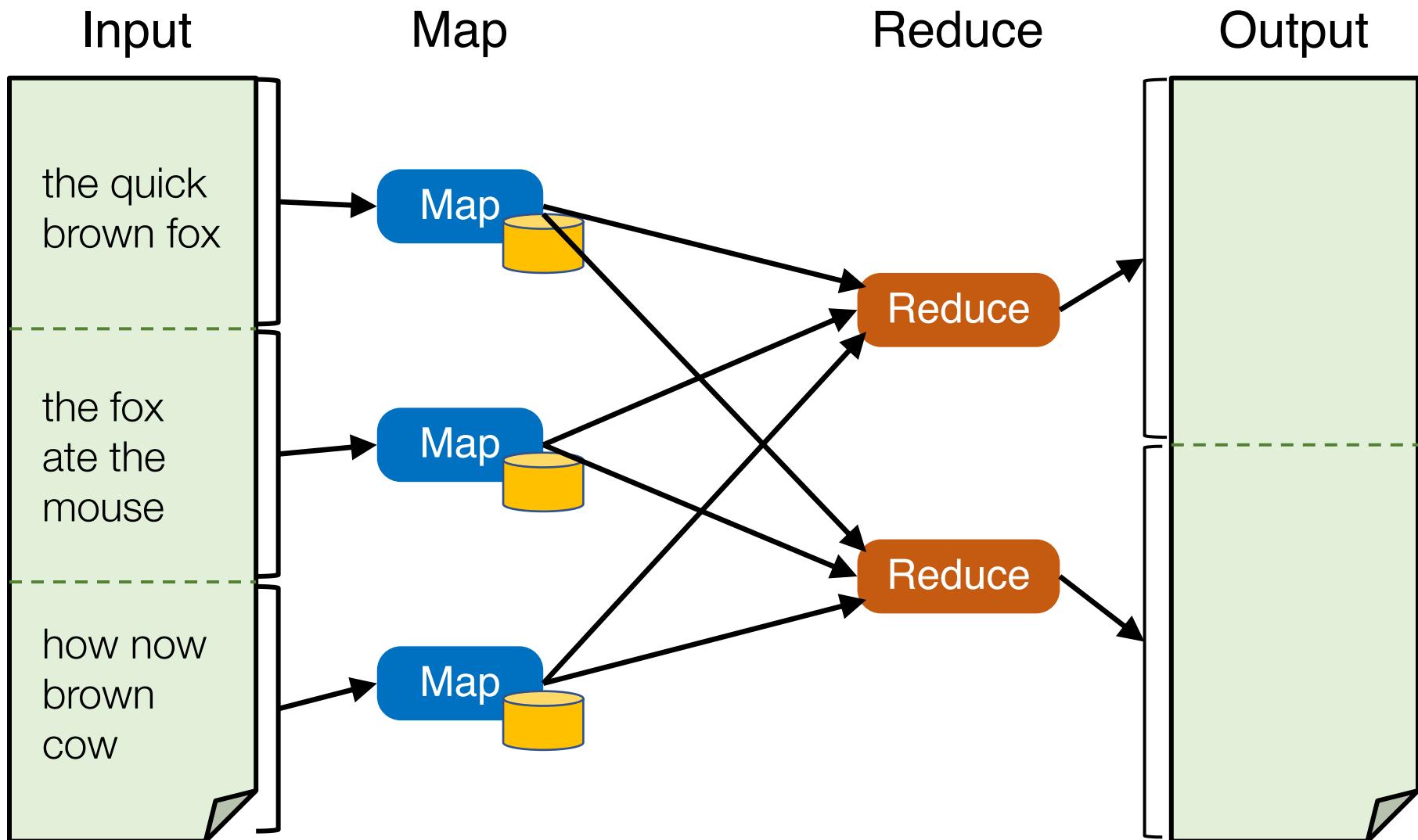
```
    int result = 0;
```

```
    for each v in values:
```

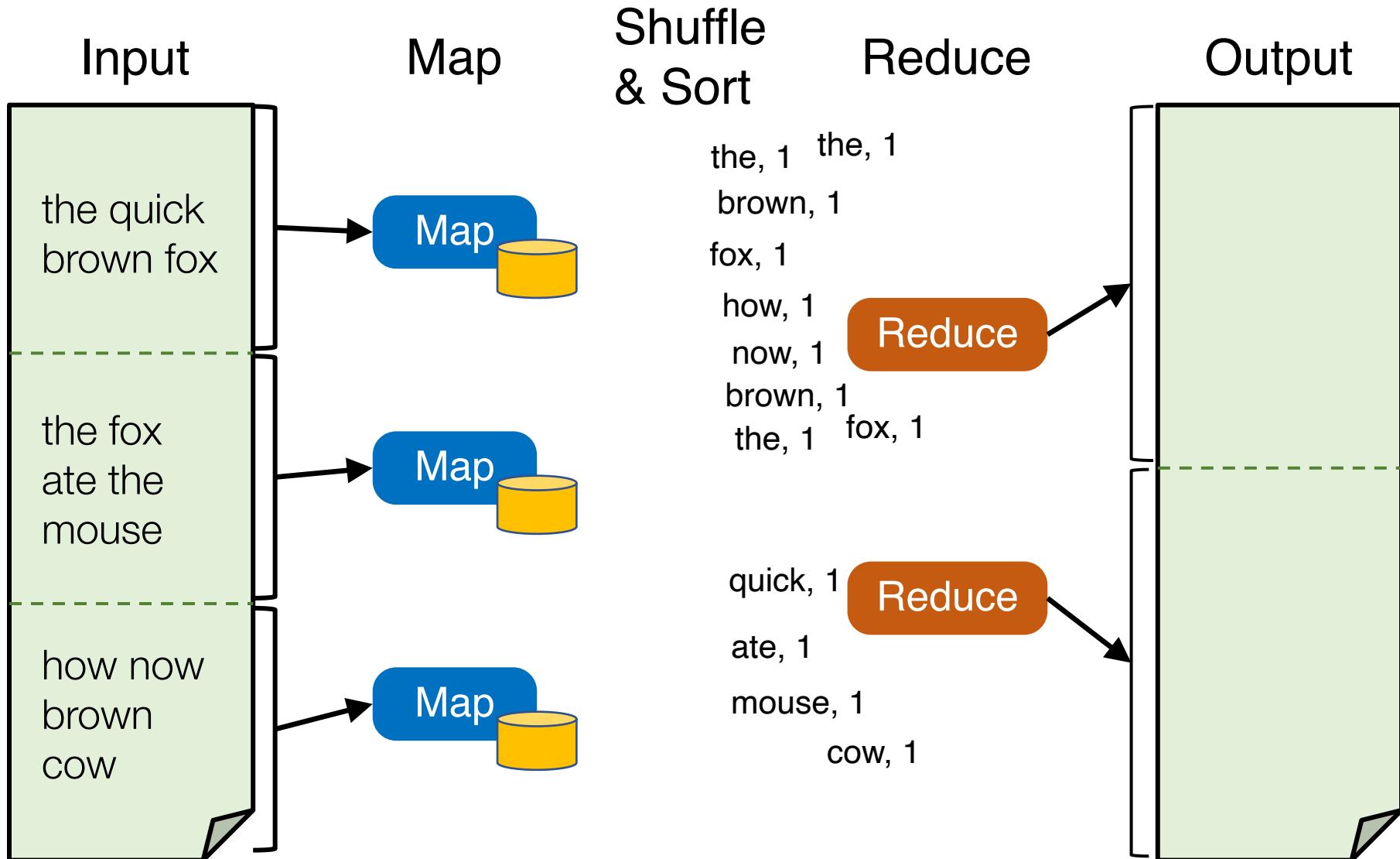
```
        results += ParseInt(v);
```

```
    Emit(AsString(result));
```

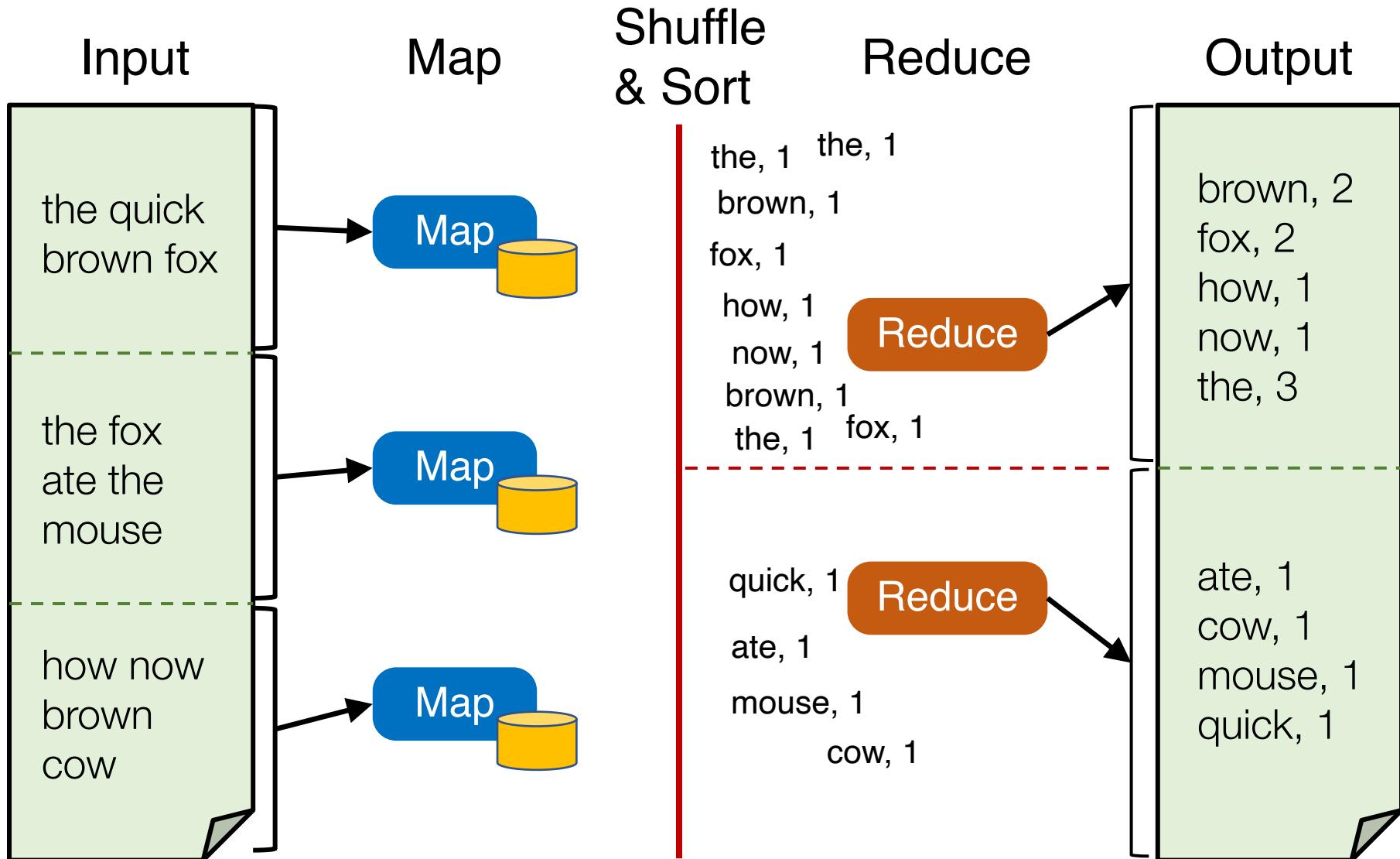
# Word Count execution



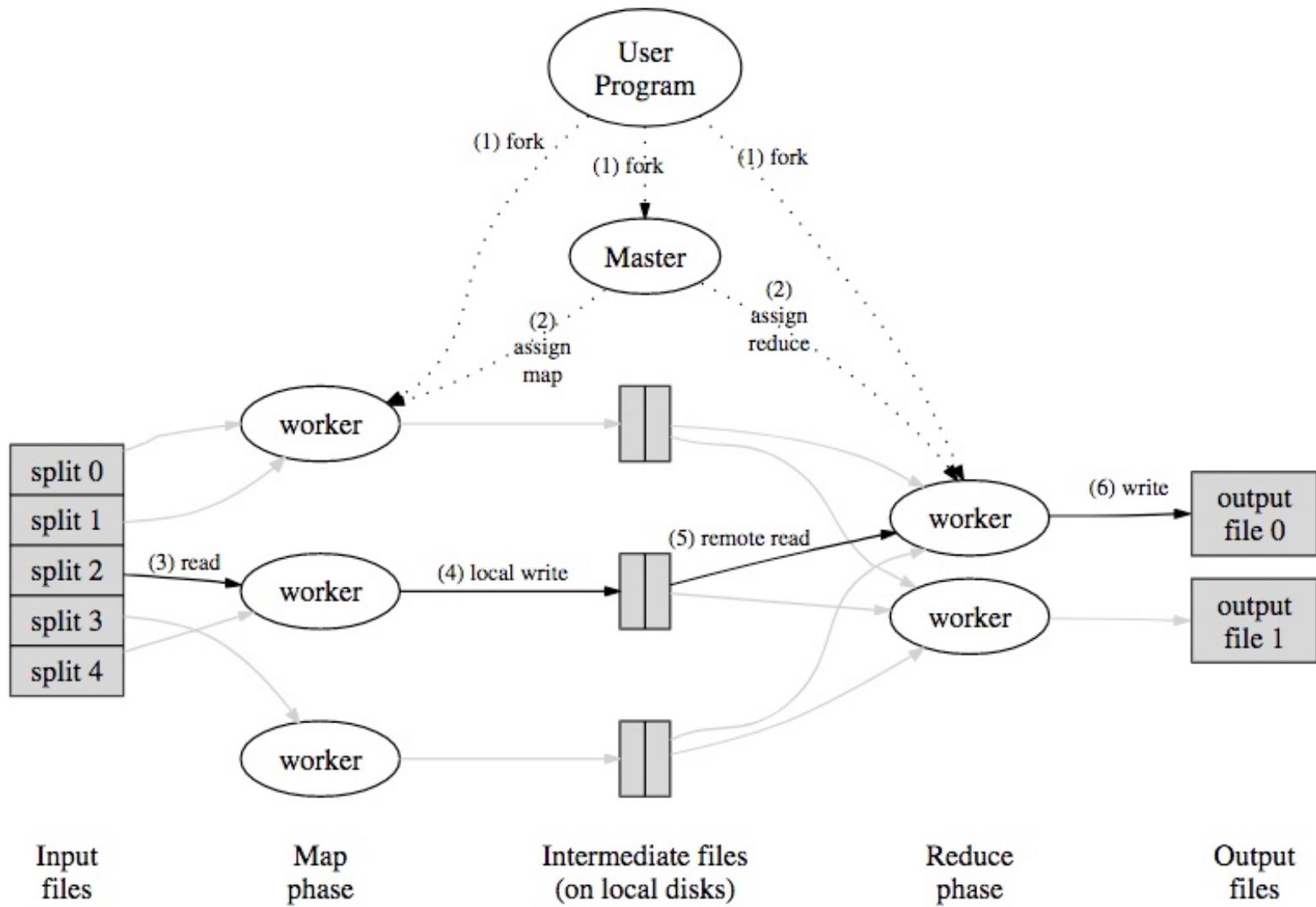
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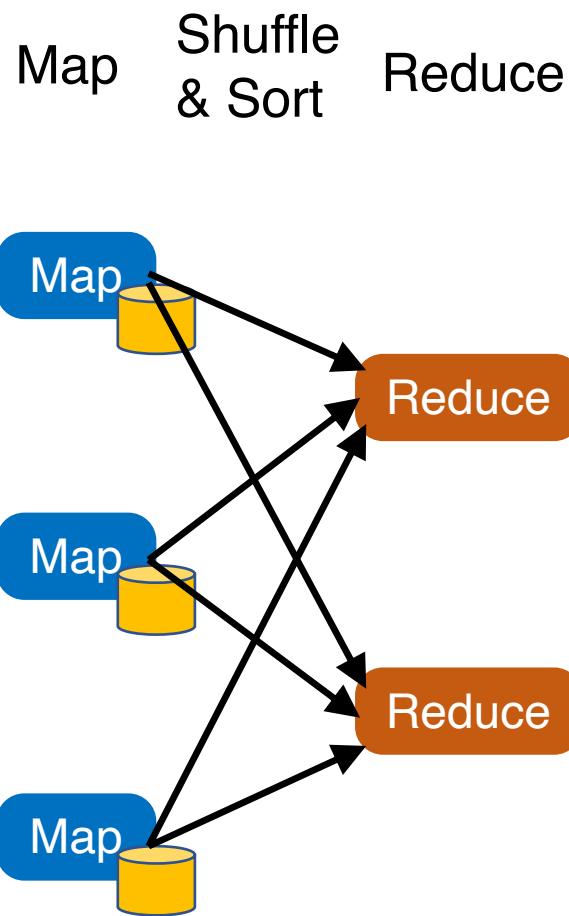
# Word Count execution



# MapReduce data flows



# MapReduce processes



- Map workers write intermediate output to local disk, separated by partitioning. Once completed, tell master node
- Reduce worker told of location of map task outputs, pulls their partition's data from each mapper, execute function across data
- Note:
  - “All-to-all” shuffle b/w mappers and reducers
  - Written to disk (“materialized”) b/w each state

# MapReduce assumptions

- Commodity hardware
  - Economies of scale!
  - Commodity networking with less bisection bandwidth
  - Commodity storage (hard disks) is cheap
- Failures are common
- Replicated, distributed file system for data storage

# Fault tolerance

- If a task crashes:
  - Retry on another node
    - Why this is okay?
  - If the same task repeatedly fails, end the job

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- If a task crashes:
  - Retry on another node
    - Why this is okay?
  - If the same task repeatedly fails, end the job
- If a node crashes:
  - Relaunch its current tasks on another node
    - What about task inputs?

# Today's outline

1. Google MapReduce
  - Google File System
2. Concurrency in Go

# Google file system (GFS)

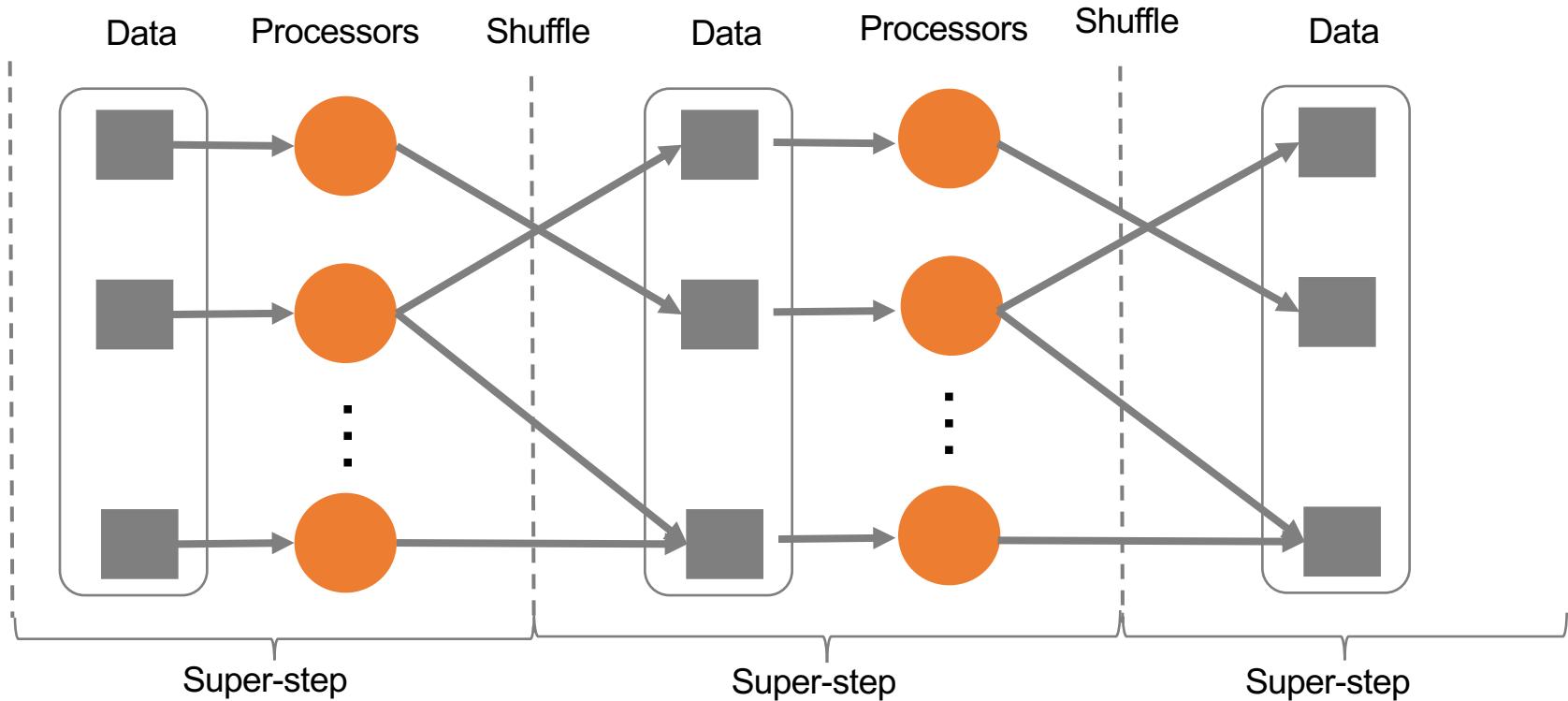
- Goal: a global (distributed) file system that stores data across many machines
  - Need to handle 100's TBs
- Google published details in 2003
- Open source implementation:
  - Hadoop Distributed File System (HDFS)



# Workload-driven design

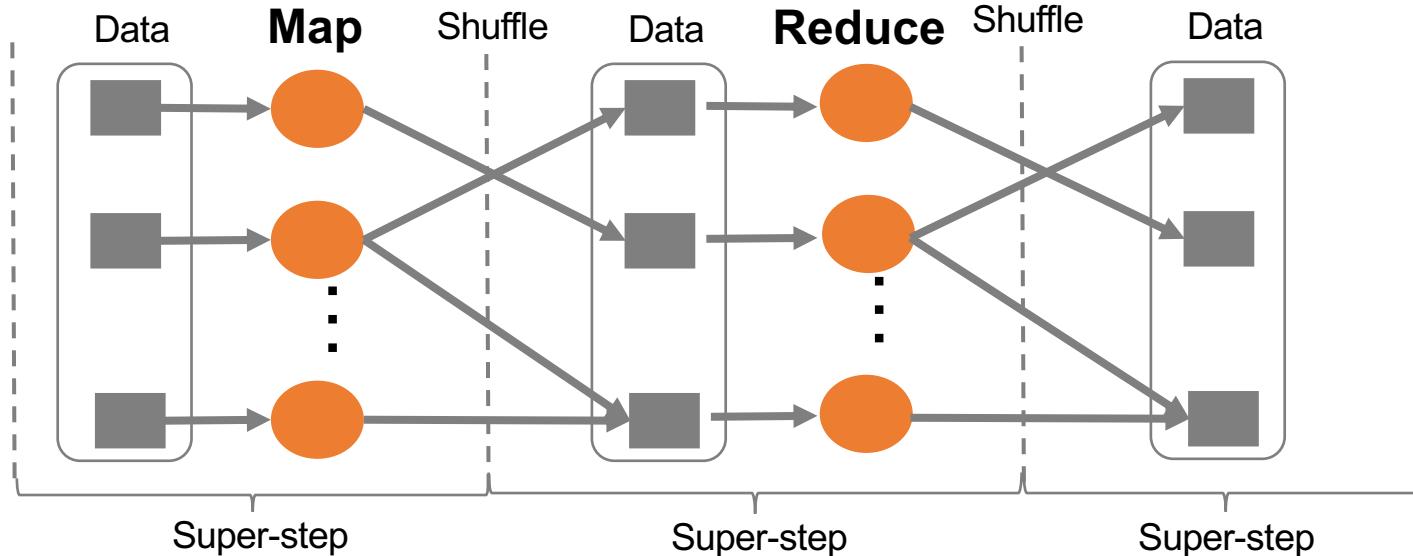
- MapReduce workload characteristics
  - Huge files (GBs)
  - Almost all writes are appends
  - Concurrent appends common
  - High throughput is valuable
  - Low latency is not

# Example workloads: Bulk Synchronous Processing (BSP)



\*Leslie G. Valiant, A bridging model for parallel computation, Communications of the ACM, Volume 33 Issue 8, Aug. 1990

# MapReduce as a BSP system

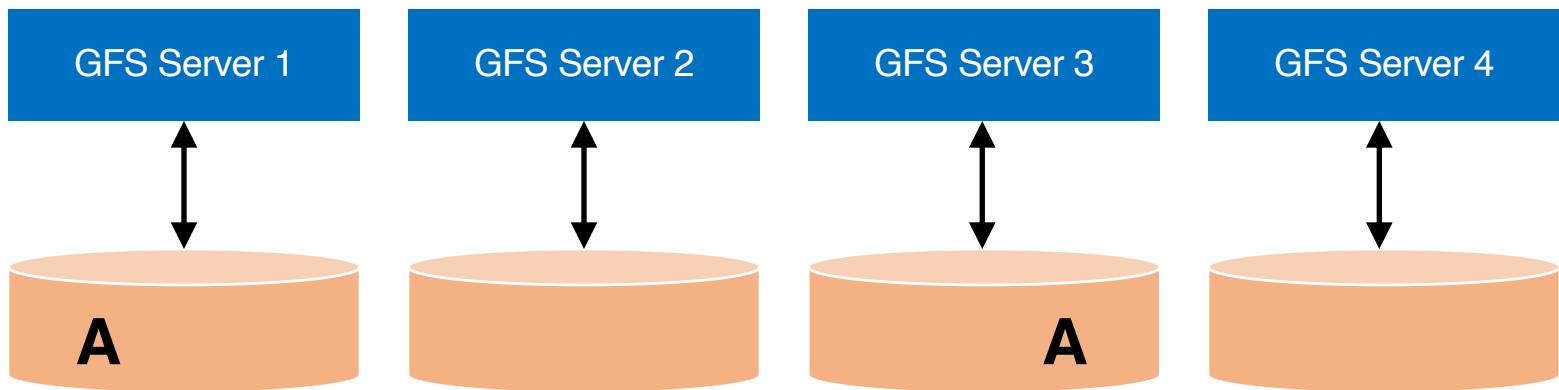


- Read entire dataset, do computation over it
  - Batch processing
- Producer/consumer: many producers append work to file concurrently; one consumer reads and does work

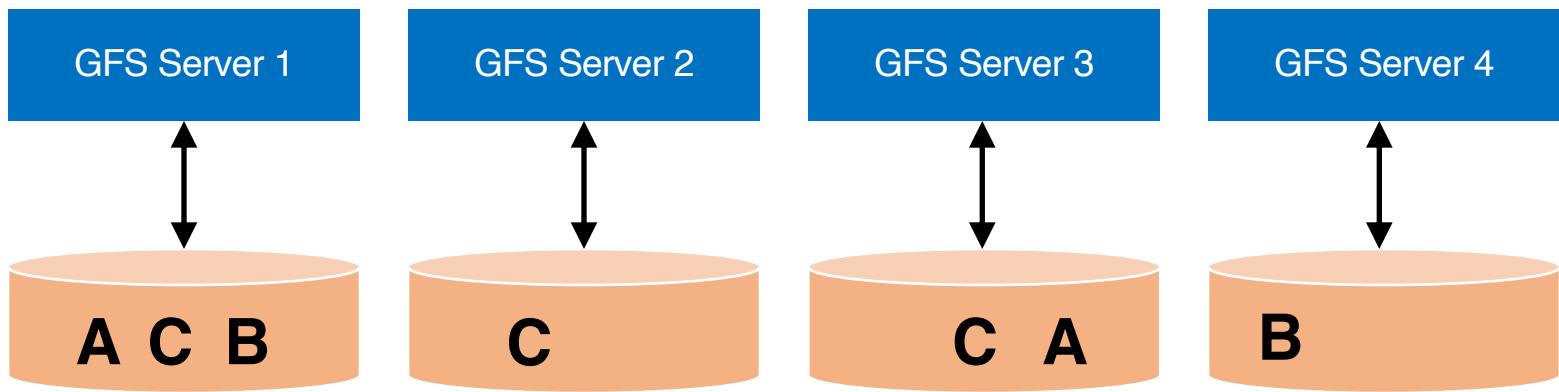
# Workload-driven design

- Build a global (distributed) file system that incorporates all these application properties
- Only supports **features required by applications**
- Avoid difficult local file system features, e.g.:
  - rename dir
  - links

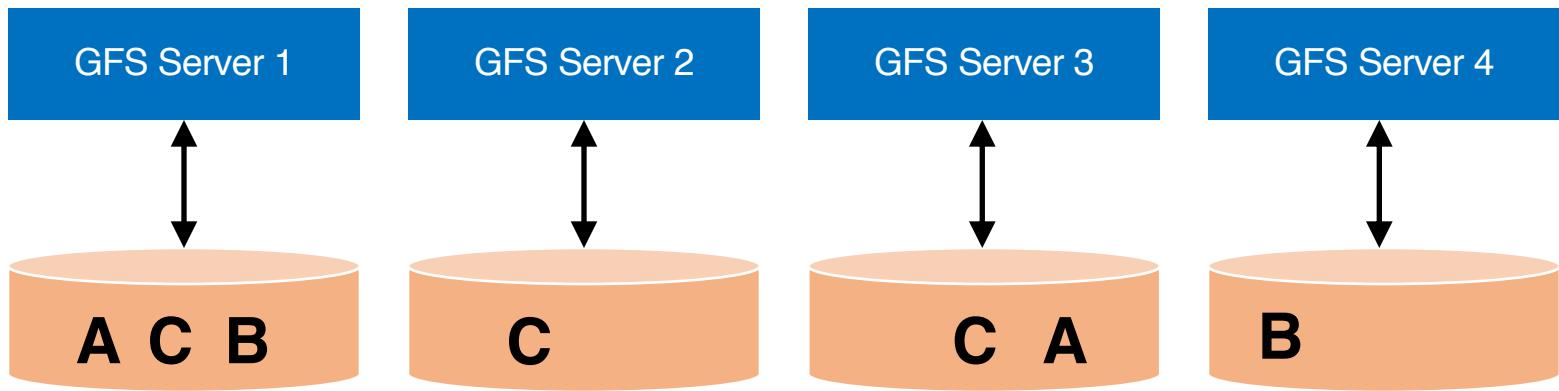
# Replication



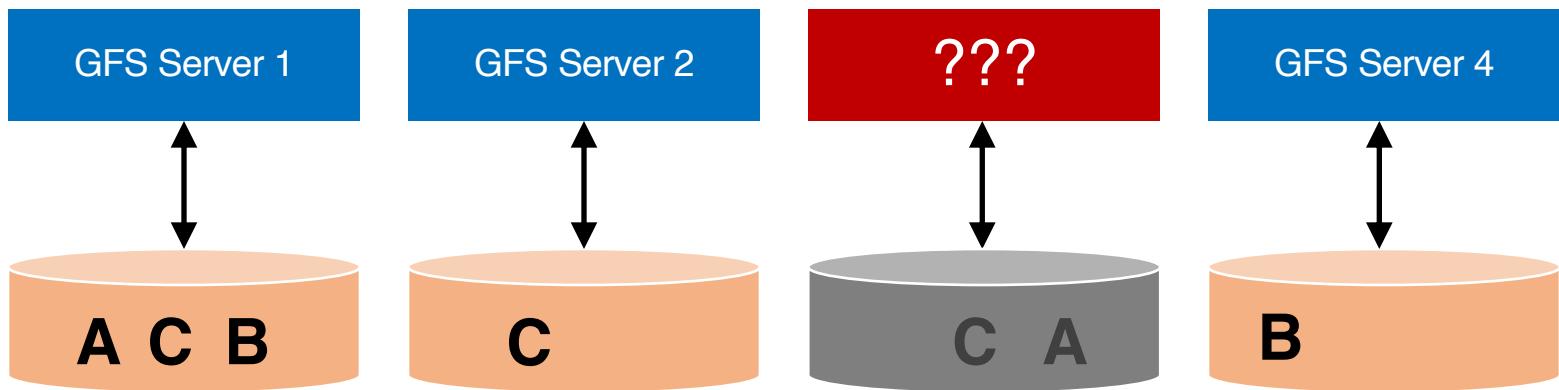
# Replication



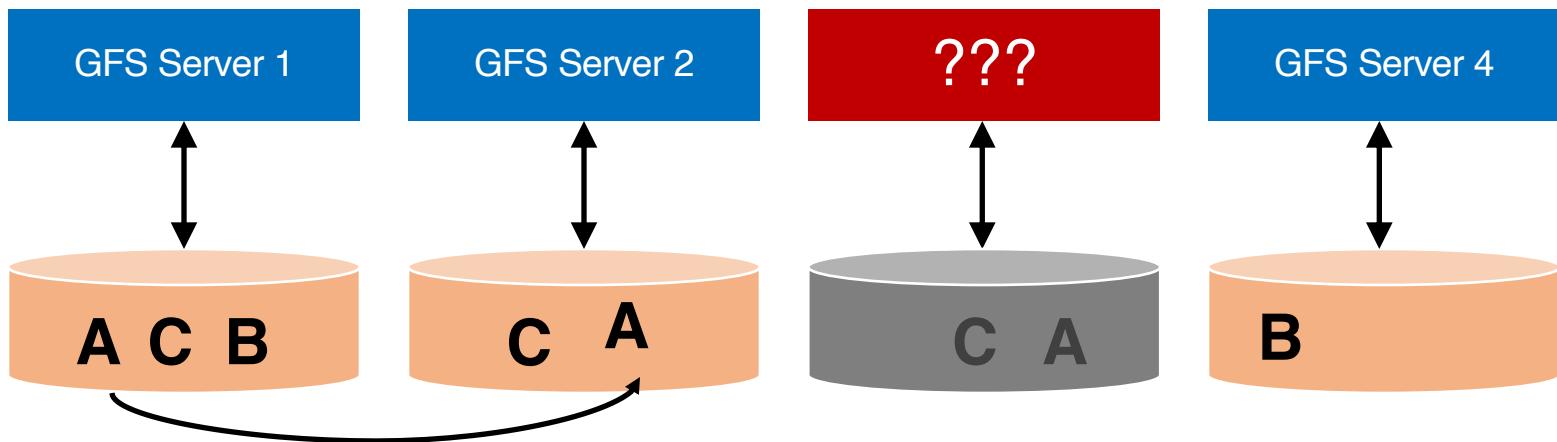
# Resilience against failures



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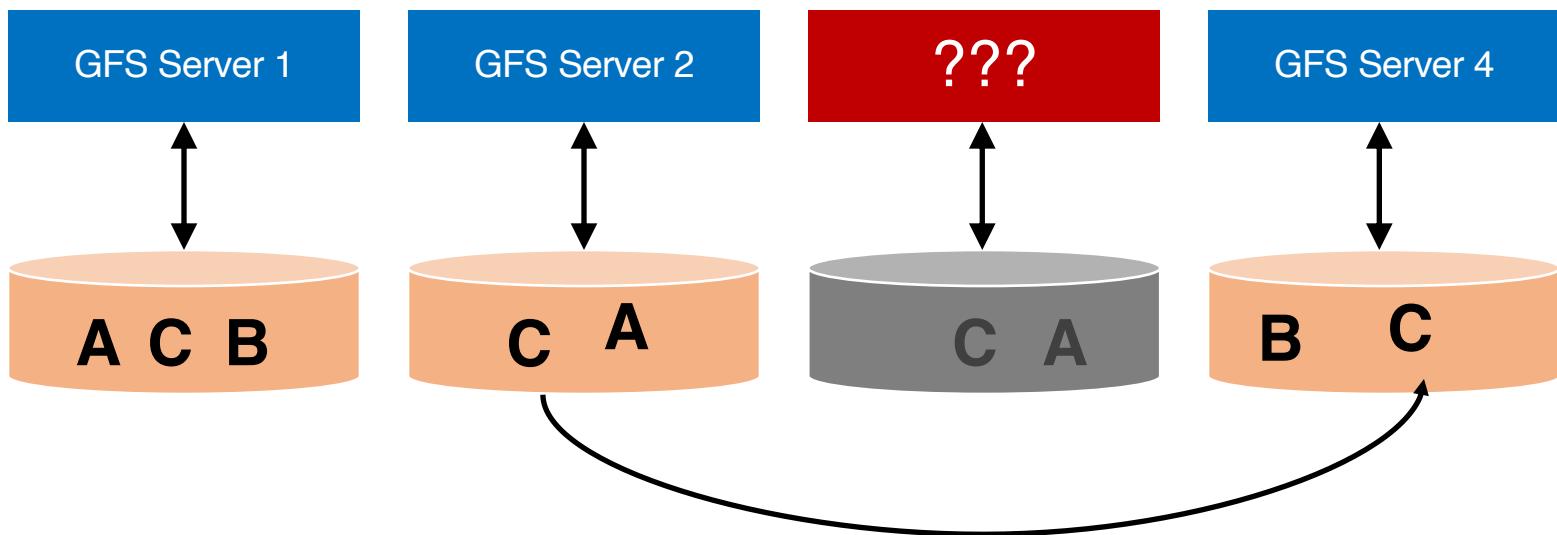


# Data Recovery



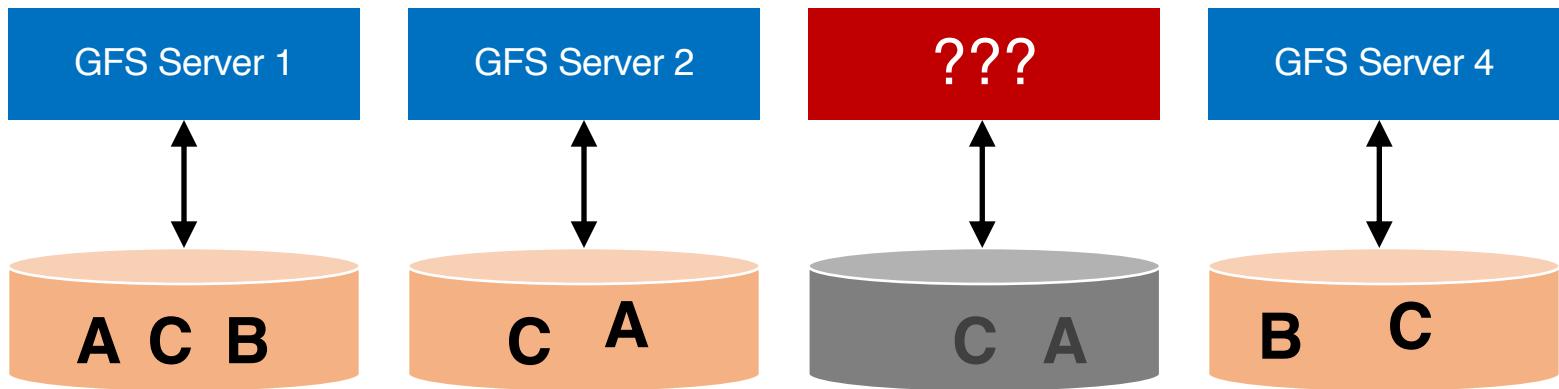
Replicating A to maintain a replication factor of 2

# Data Recovery



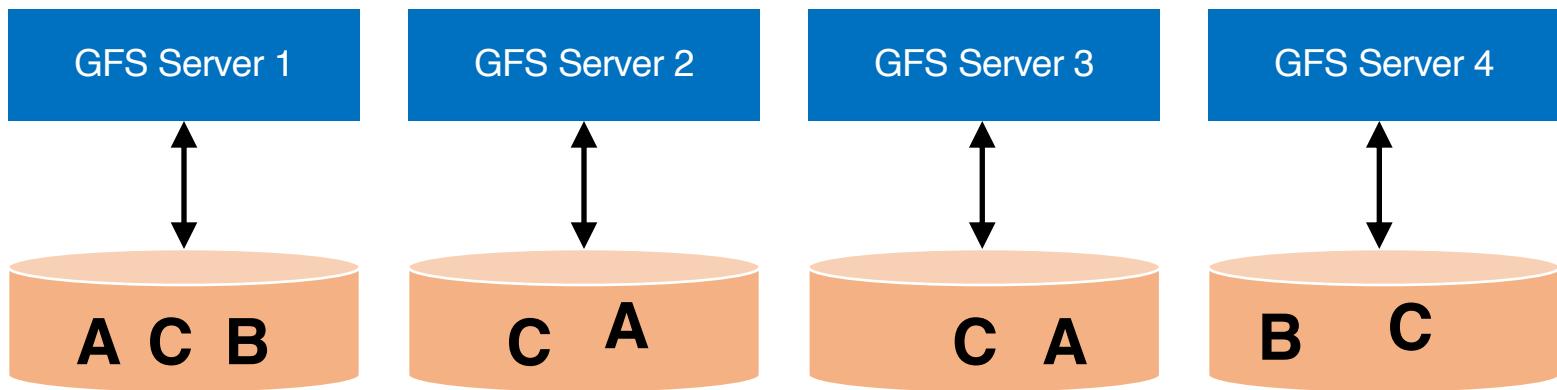
Replicating C to maintain a replication factor of 3

# Data Recovery



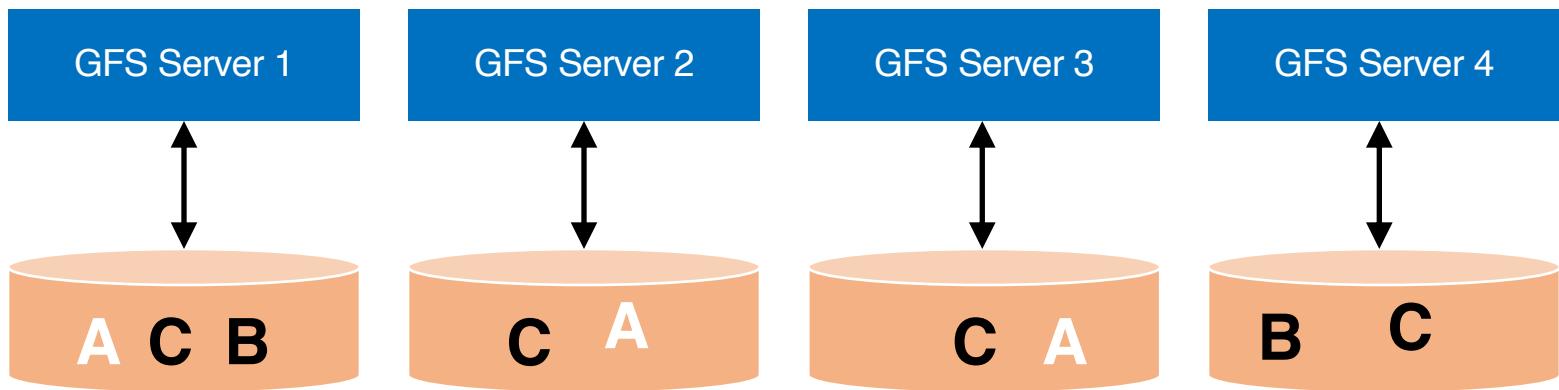
Machine may be dead forever, or it may come back

# Data Recovery

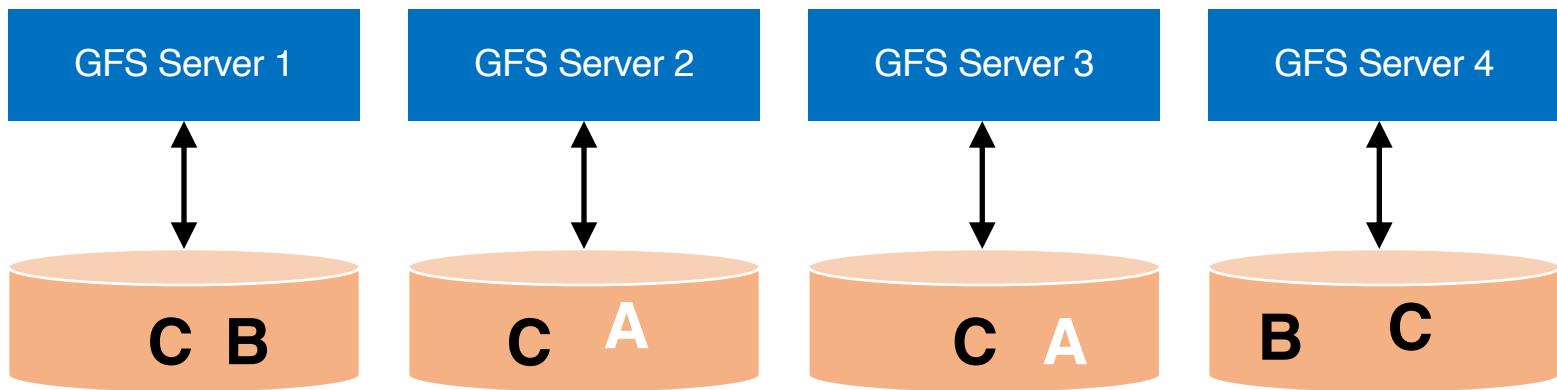


Machine may be dead forever, or it may come back

# Data Recovery



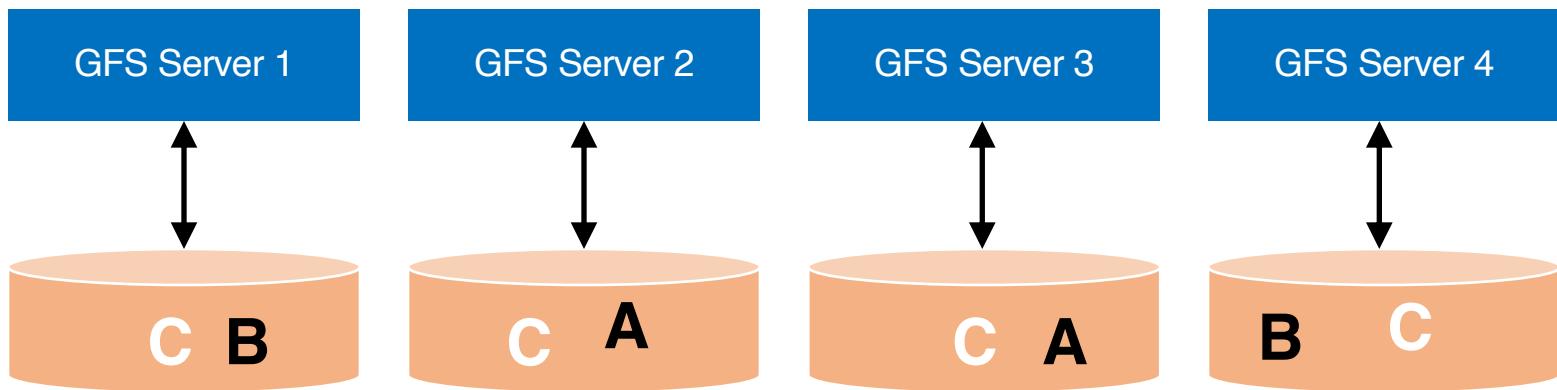
# Data Recovery



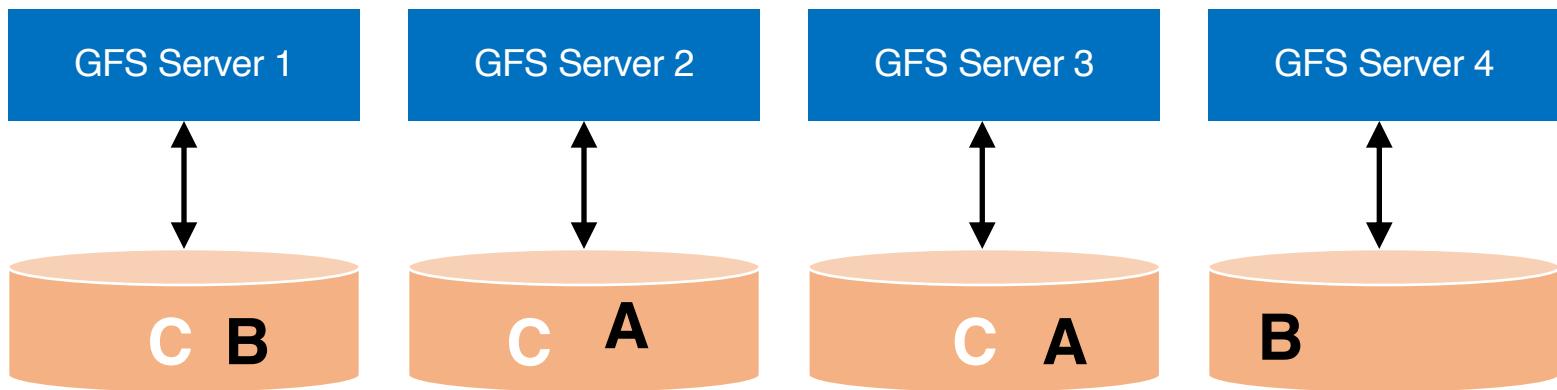
## Data Rebalancing

Deleting one A to maintain a replication factor of 2

# Data Recovery



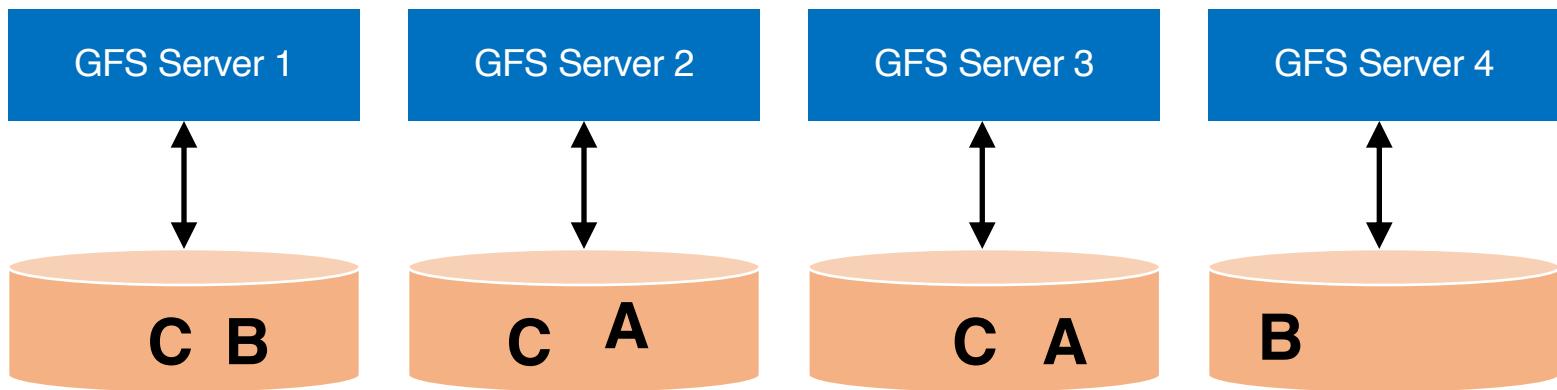
# Data Recovery



## Data Rebalancing

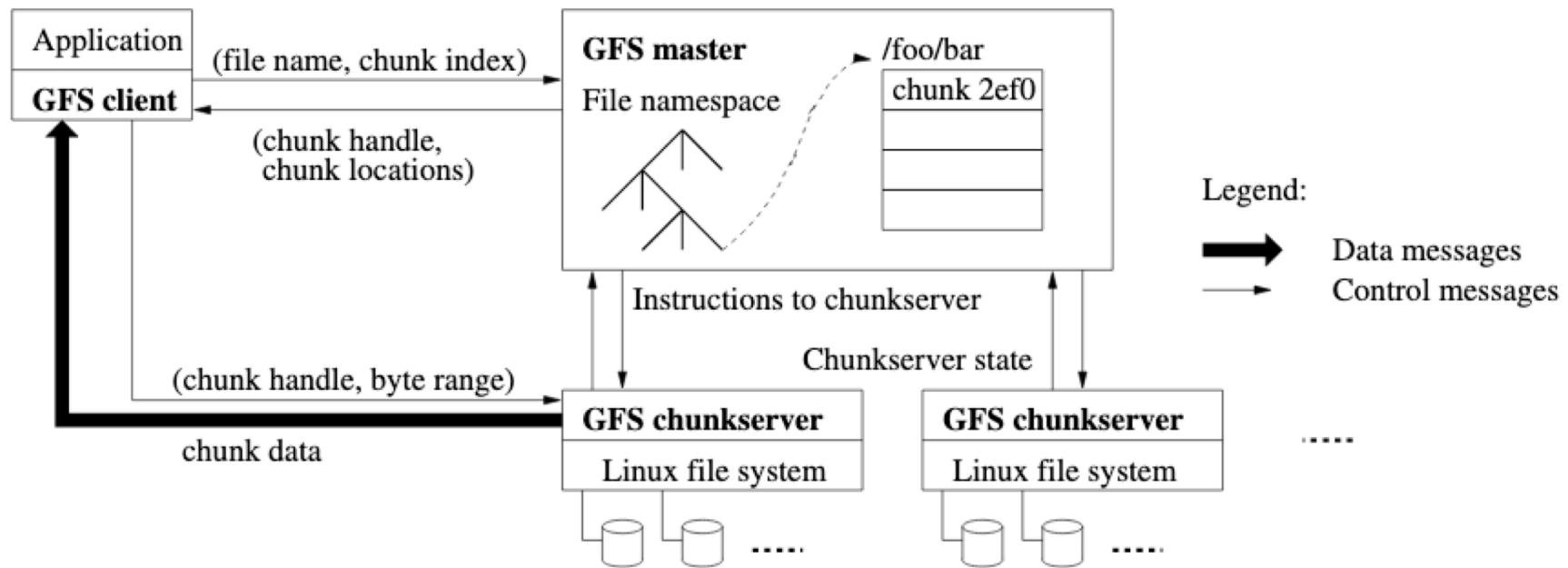
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# Data Recovery

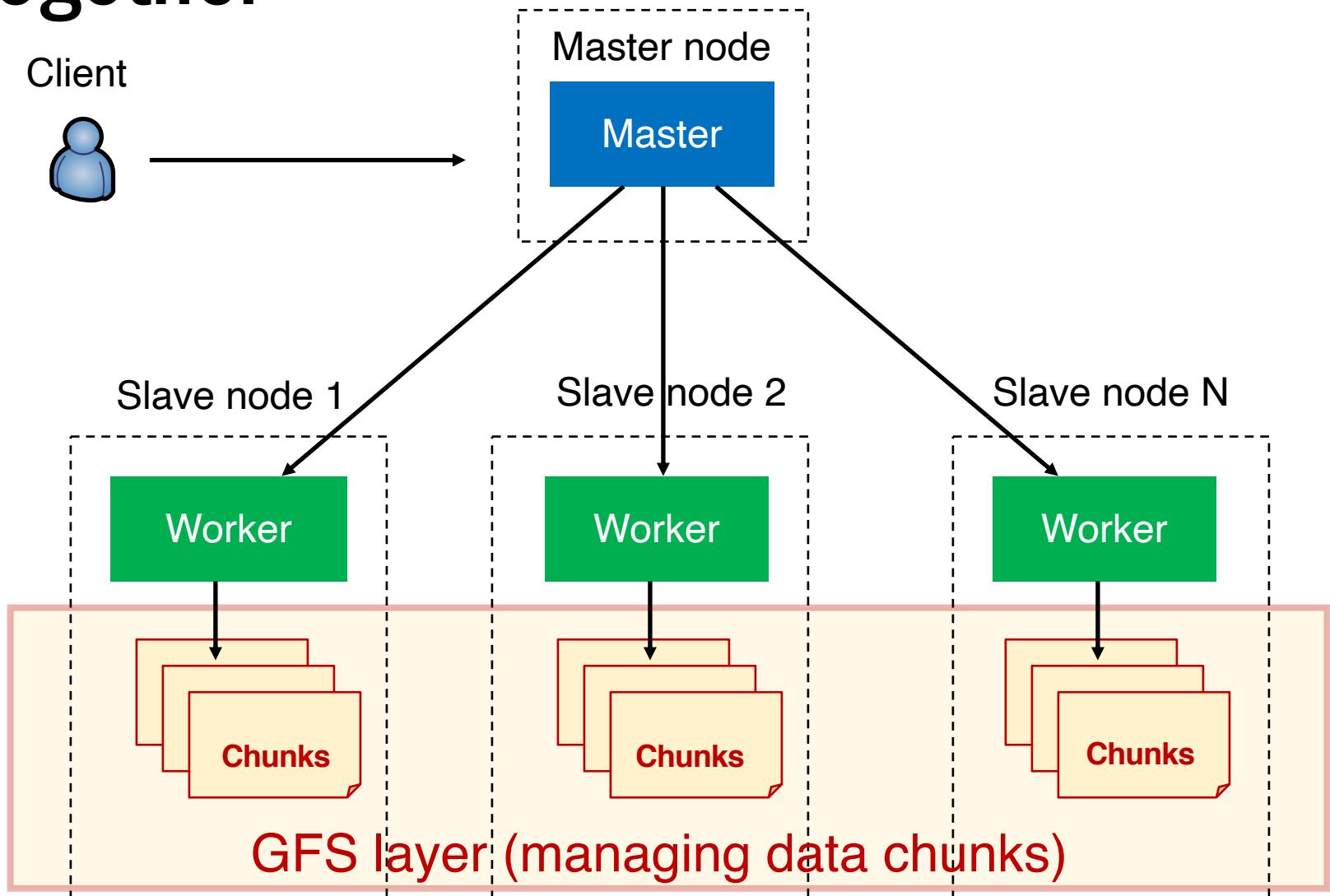


**Question:** how to maintain a global view of all data distributed across machines?

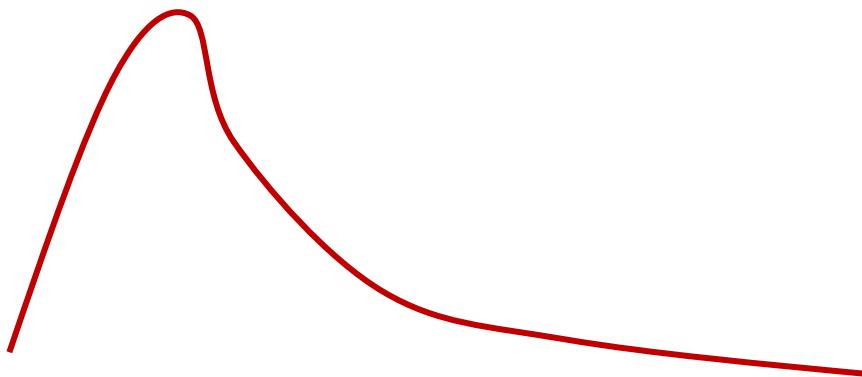
# GFS architecture



# MapReduce+GFS: Put everything together

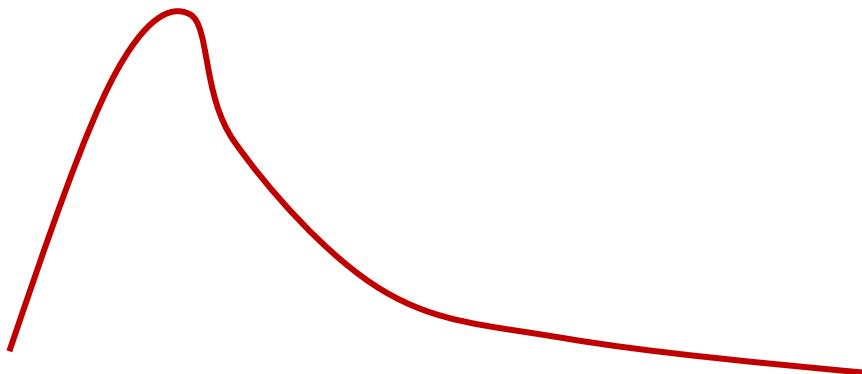


# Stragglers



Map task completion time distribution

# Stragglers



Map task completion time distribution

- Tail latency means some workers (always) finish late
- Q: How can MR work around this?
  - Hint: its approach to **fault-tolerance** provides the right tool

# Resilience against stragglers

- If a task is going slowly (i.e., **straggler**):
  - Launch second copy of task on another node
  - Take the output of whichever finishes first

# More design

- Master failure
- Locality
- Task granularity

# GFS usage at Google

- 200+ clusters
- Many clusters of 1000s of machines
- Pools of 1000s of clients
- 4+ PB filesystems
- 40 GB/s read/write load
  - In the presence of frequent hardware failures

\* Jeff Dean, LADIS 2009

# MapReduce usage statistics over time

|                                | Aug, '04 | Mar, '06 | Sep, '07 | Sep, '09 |
|--------------------------------|----------|----------|----------|----------|
| Number of jobs                 | 29K      | 171K     | 2,217K   | 3,467K   |
| Average completion time (secs) | 634      | 874      | 395      | 475      |
| Machine years used             | 217      | 2,002    | 11,081   | 25,562   |
| Input data read (TB)           | 3,288    | 52,254   | 403,152  | 544,130  |
| Intermediate data (TB)         | 758      | 6,743    | 34,774   | 90,120   |
| Output data written (TB)       | 193      | 2,970    | 14,018   | 57,520   |
| Average worker machines        | 157      | 268      | 394      | 488      |

\* Jeff Dean, LADIS 2009

# MapReduce discussion

<https://piazza.com/class/k5shuiyl7ur79q?cid=14>

# MapReduce discussion

- What will likely serve as a performance bottleneck for Google's MapReduce used back in 2004 (or even earlier)? CPU? Memory? Disk? Network? Anything else?

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- What will likely serve as a performance bottleneck for Google's MapReduce used back in 2004 (or even earlier)? CPU? Memory? Disk? Network? Anything else?
- How does MapReduce reduce the effect of slow network?

# MapReduce discussion

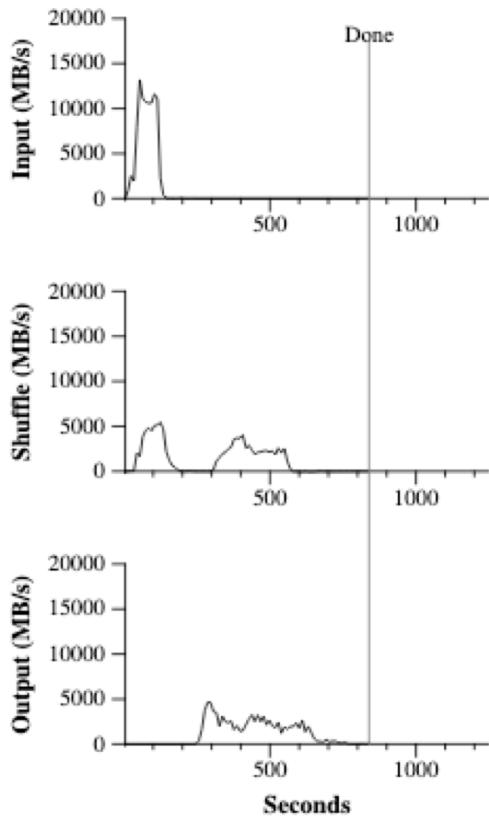
- How does MapReduce jobs get good load balance across worker machines?

# MapReduce discussion

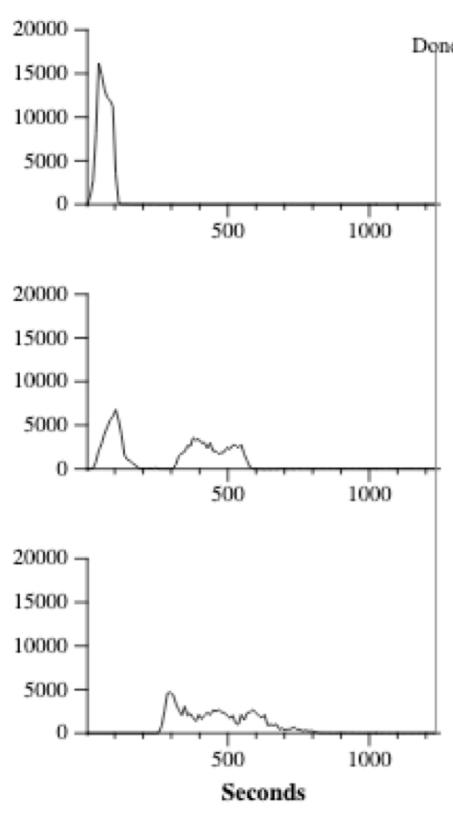
- Consider the indexing pipeline where you start with HTML documents. You want to index the documents after removing the most commonly occurring words:
  1. Compute the most common words;
  2. Remove them and build the index

What are the main shortcomings of using MapReduce to support such pipeline-like applications?

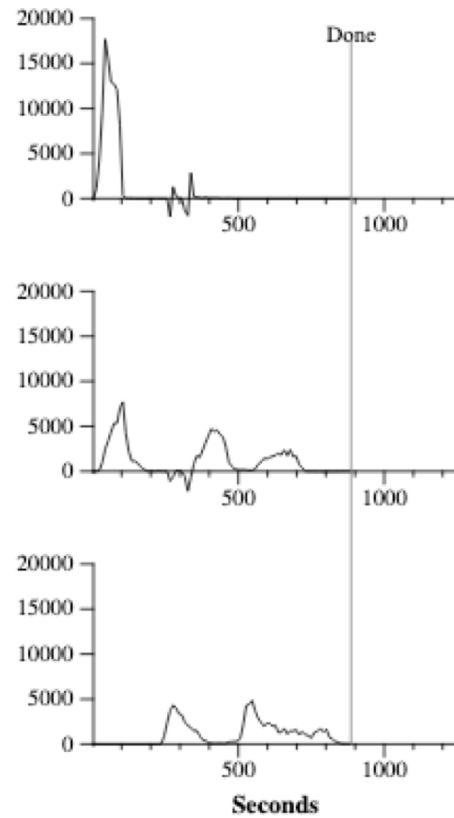
# MapReduce discussion



(a) Normal execution



(b) No backup tasks



(c) 200 tasks killed

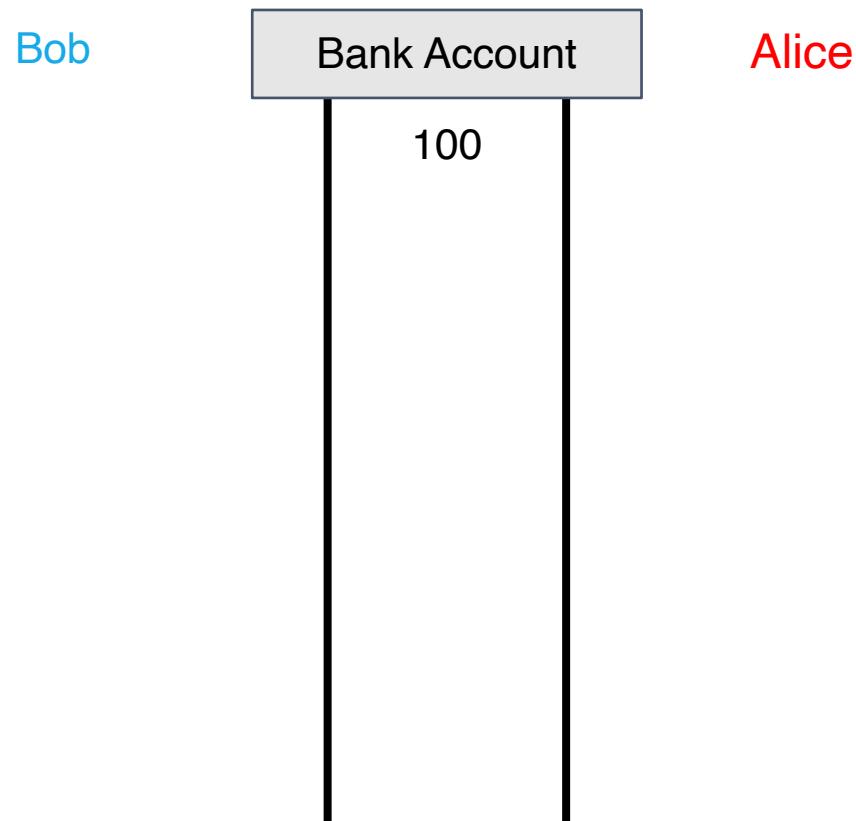
# Today's outline

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  - Two synchronization mechanisms
    - Locks
    - Channels

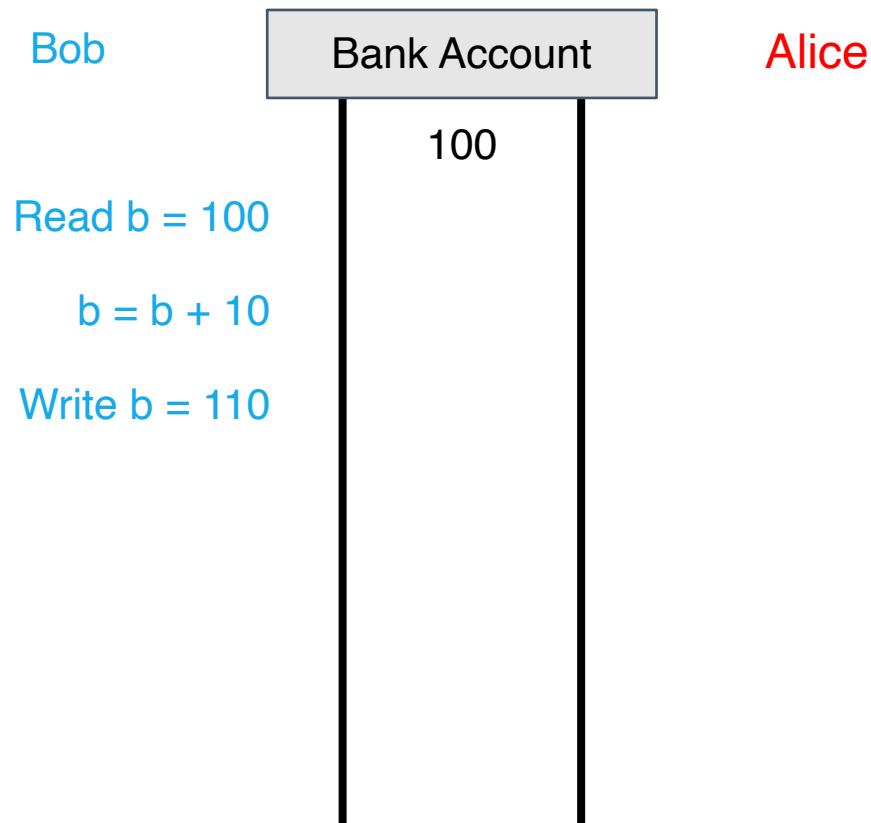
# Two synchronization mechanisms in Go

- **Locks:** limit access to a critical section
  - Access to a critical section (e.g., shared variables) must be mutually exclusive
- **Channels:** pass information across threads using a queue

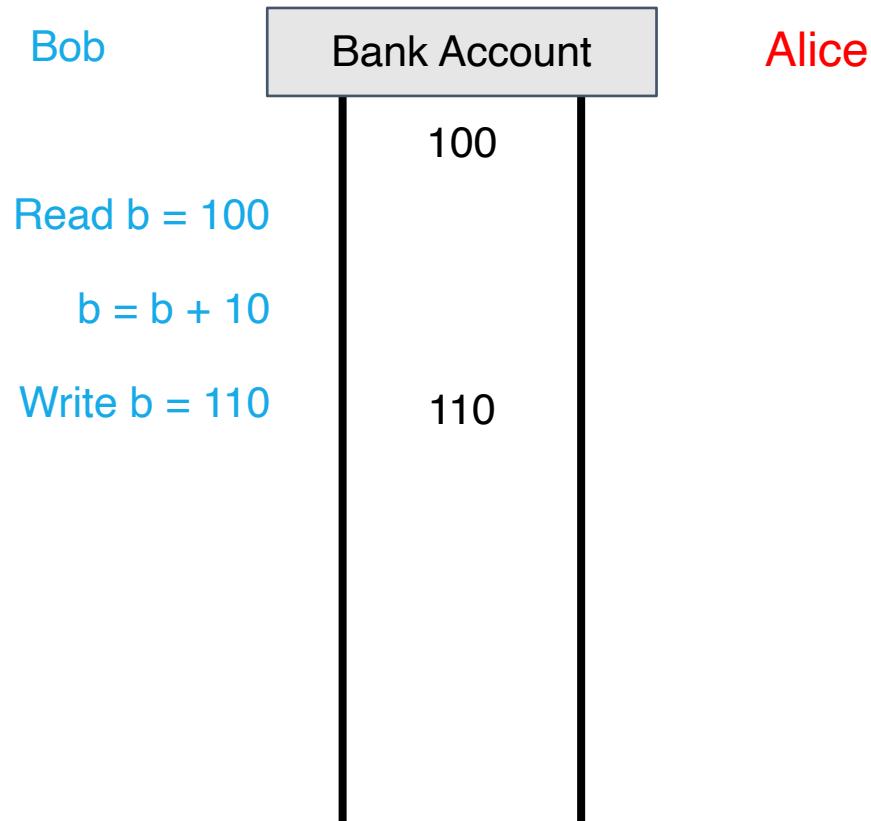
# Example: Bank account



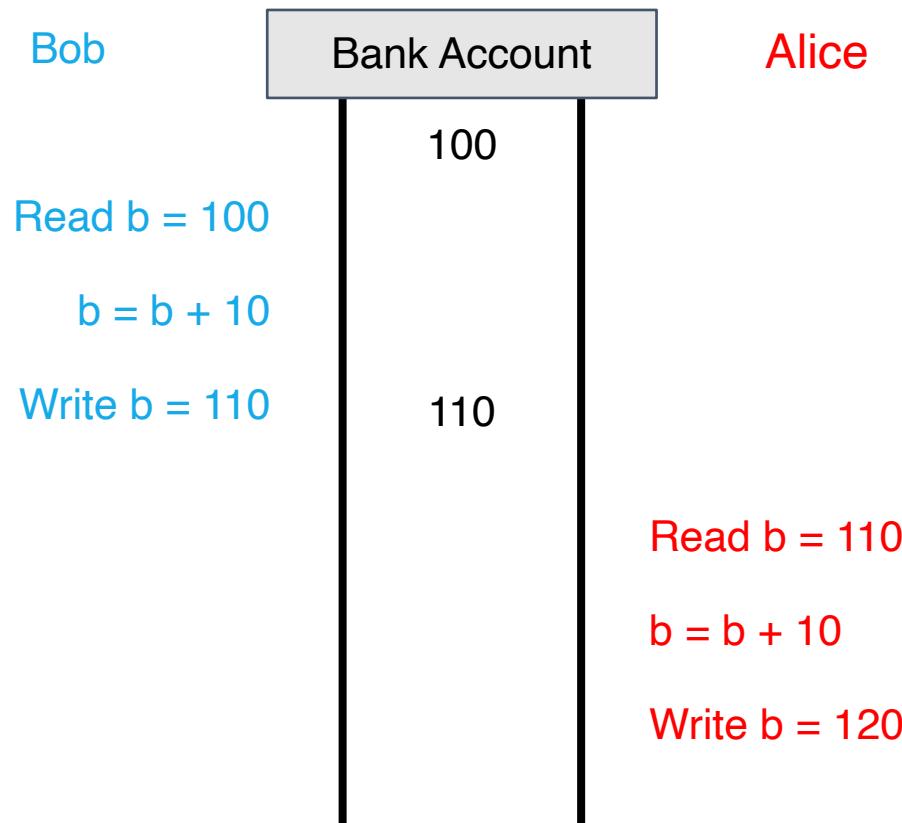
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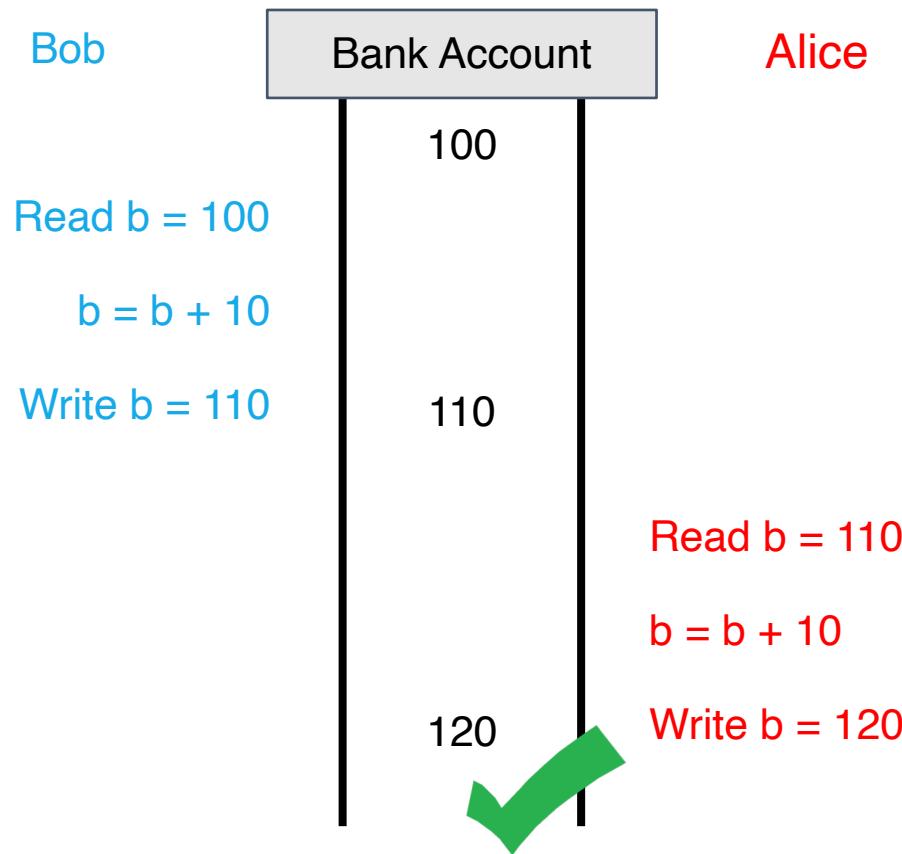
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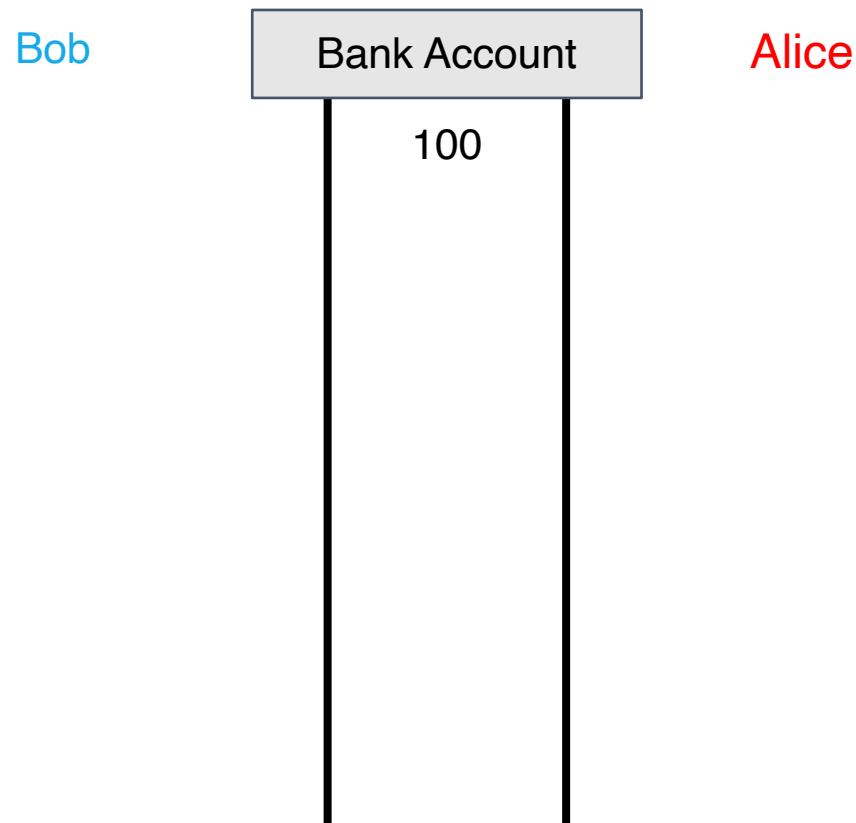
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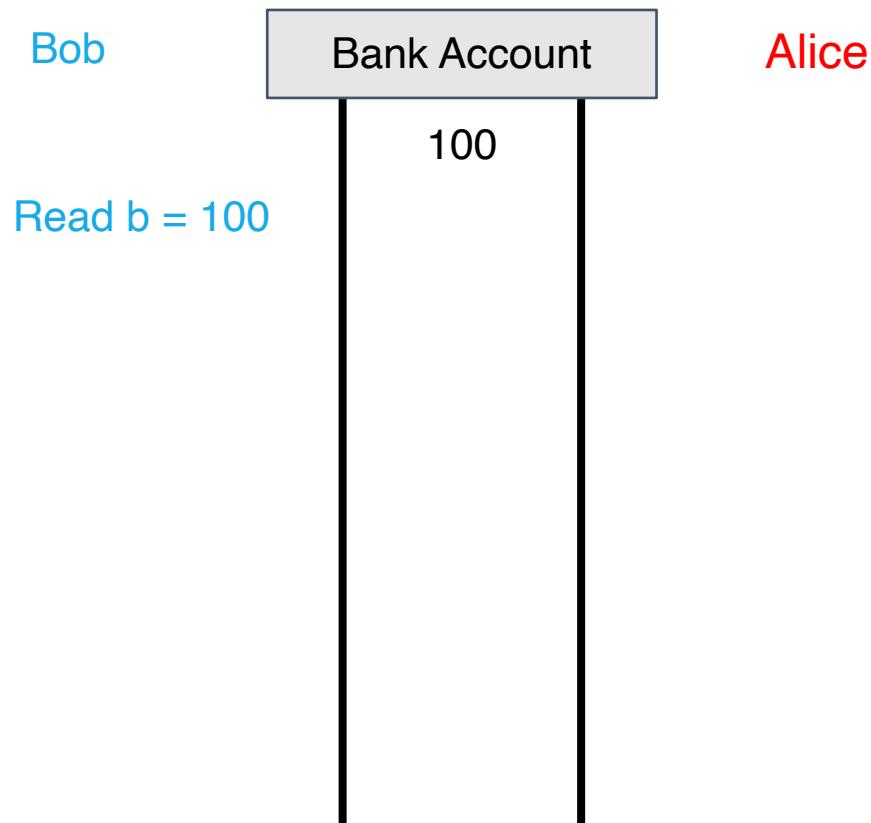
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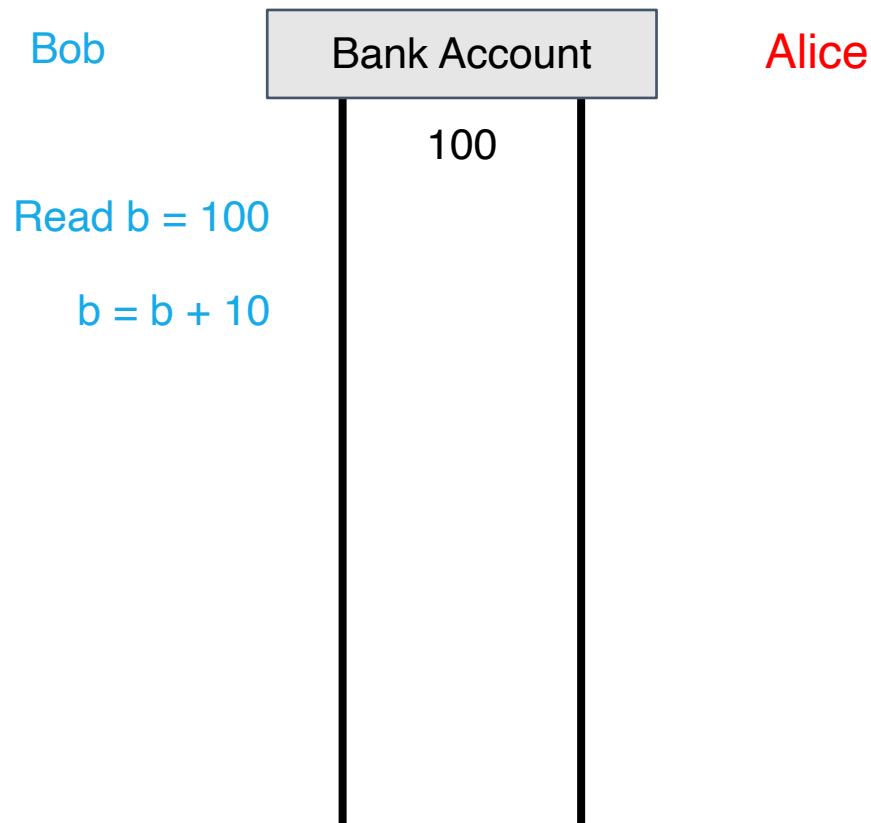
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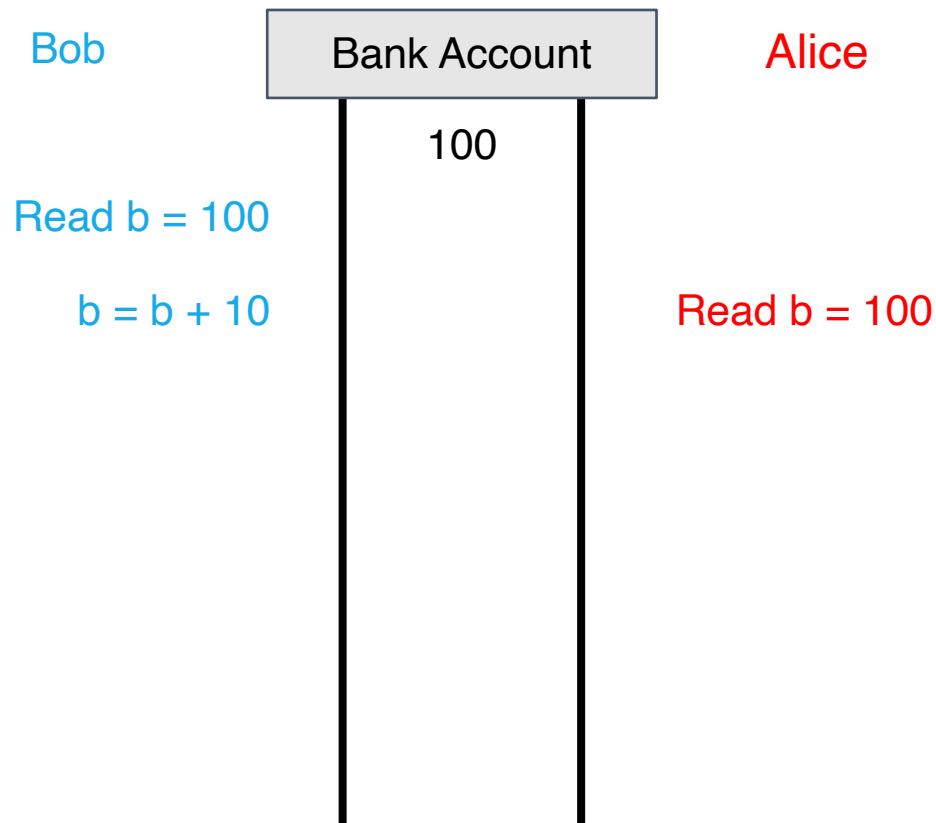
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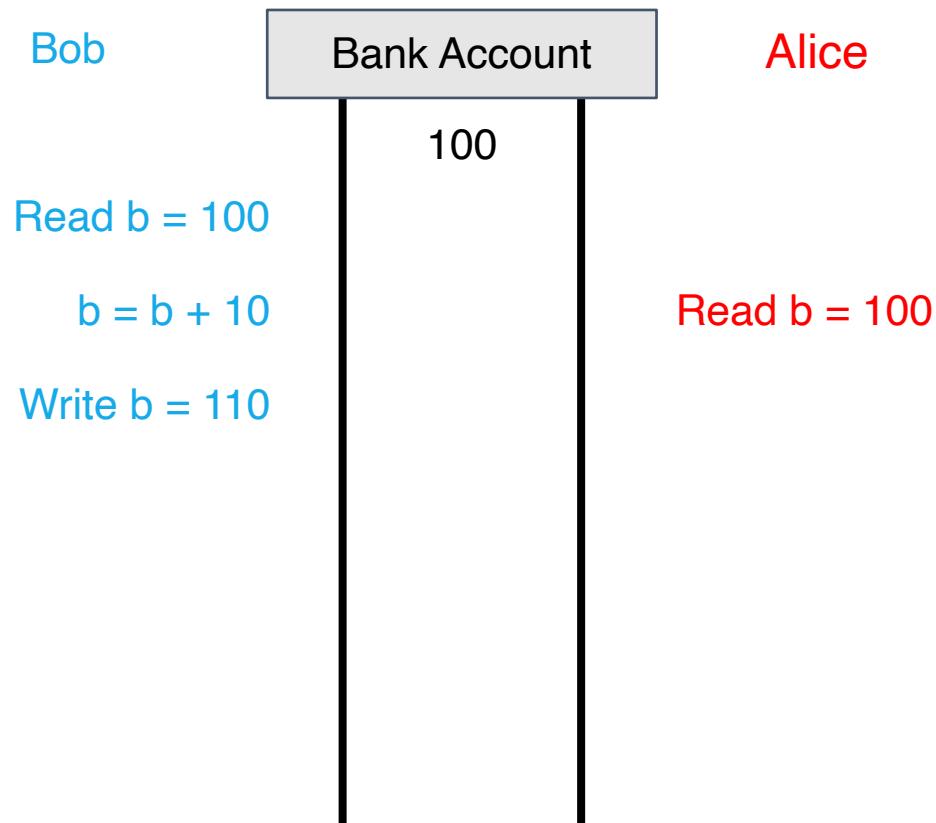
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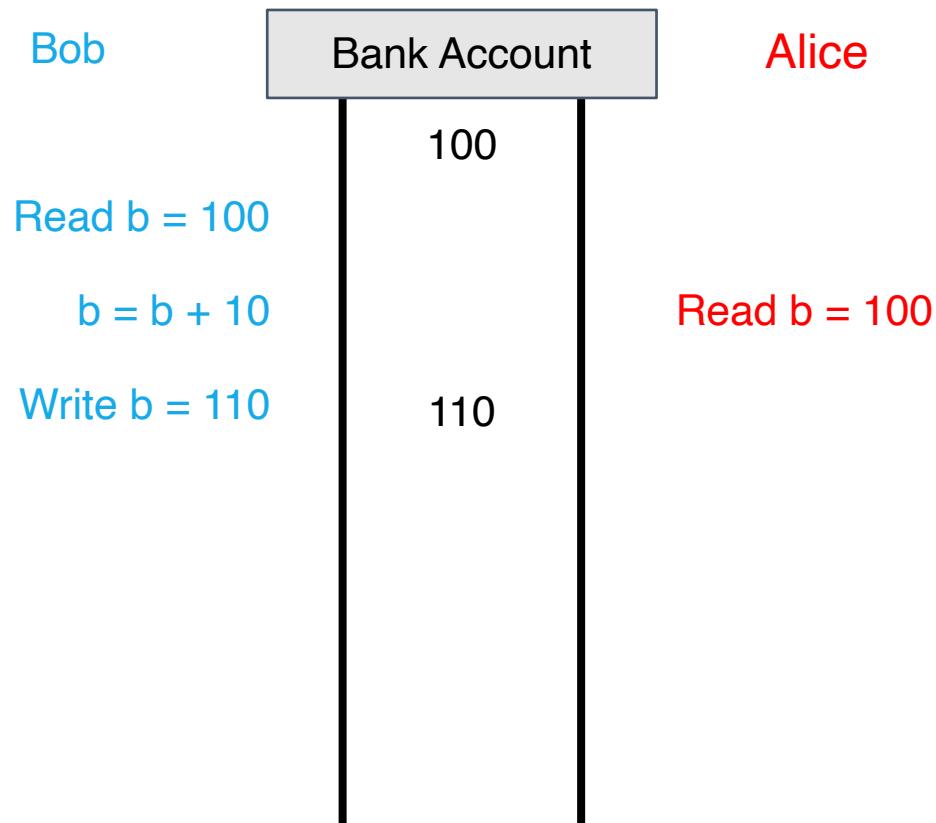
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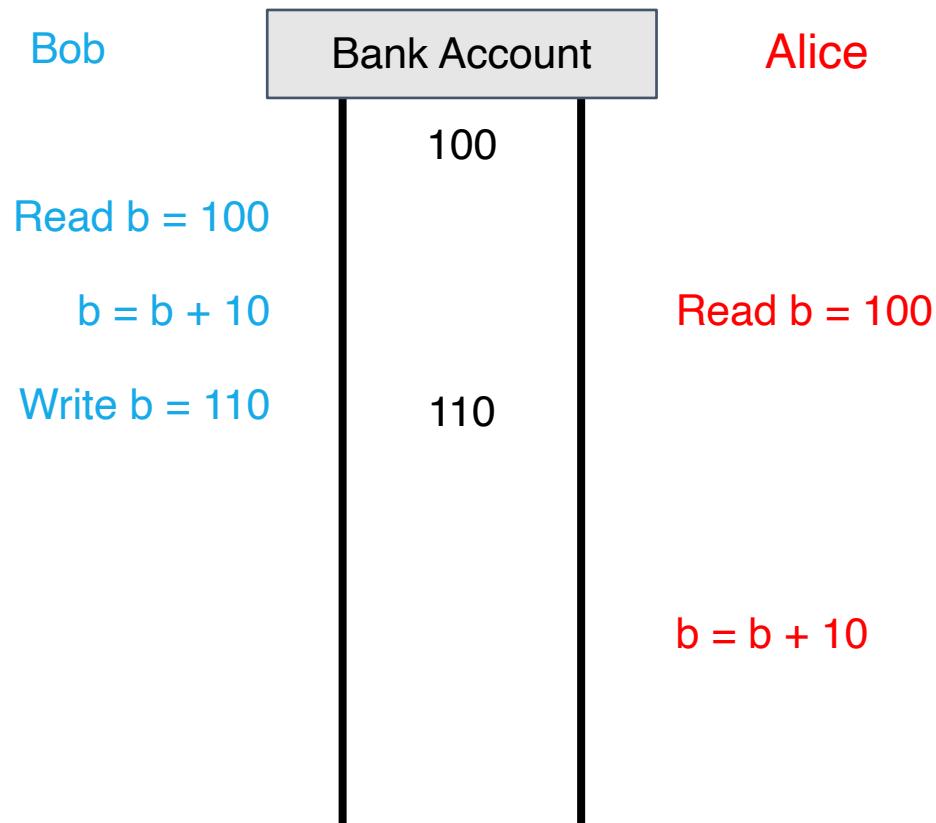
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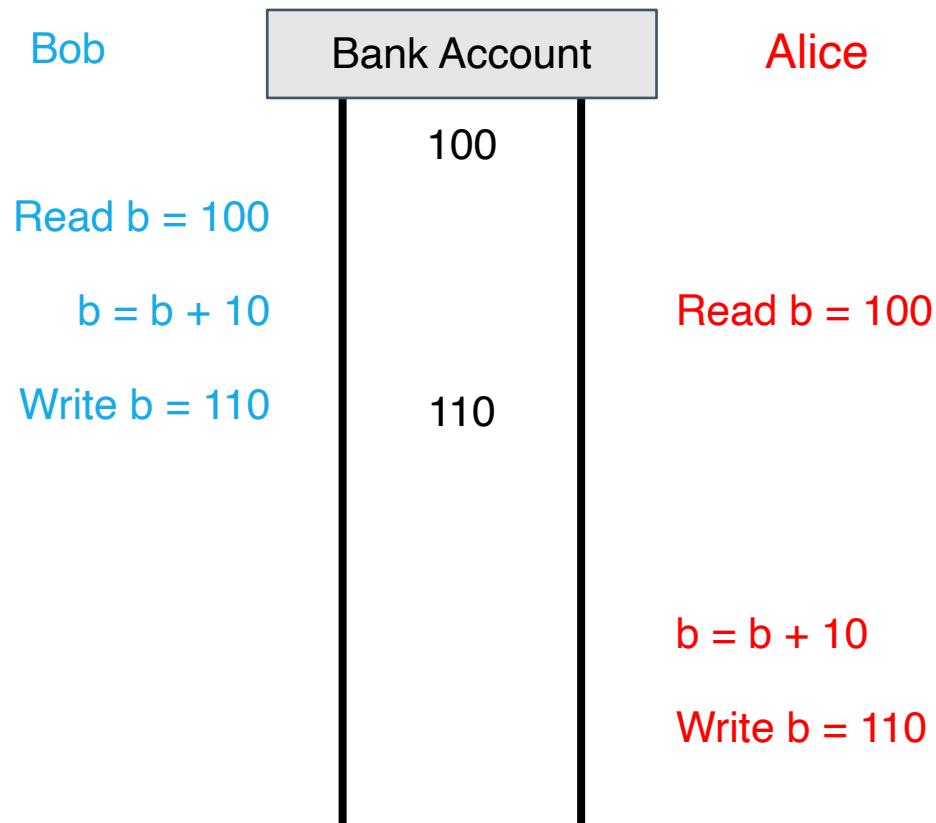
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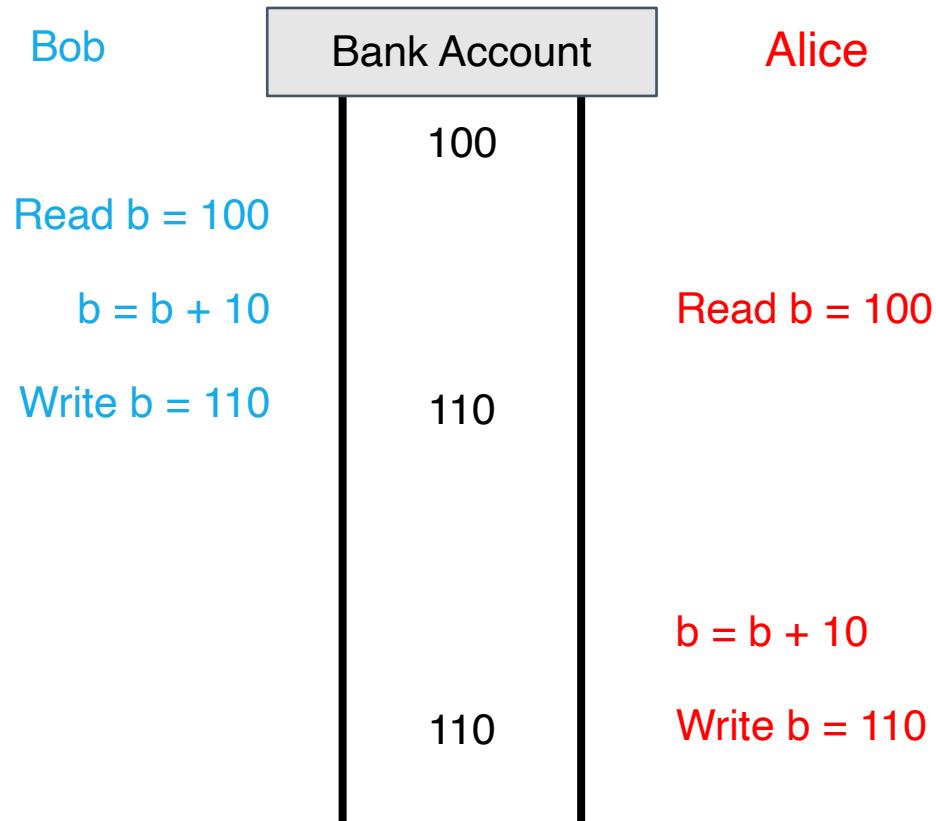
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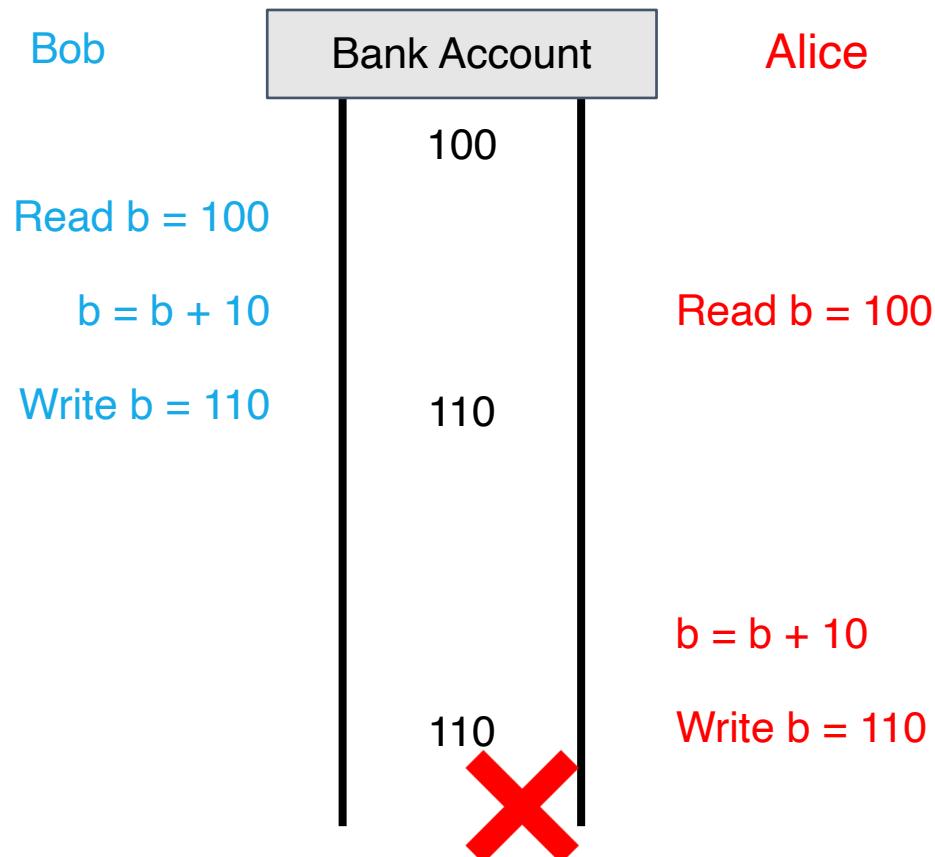
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# What went wrong?

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```
func Deposit(amount) {  
    lock balanceLock  
    read balance  
    balance = balance + amount  
    write balance  
    unlock balanceLock  
}
```

# What went wrong?

- Changes to balance are not *atomic*

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*Critical  
section*

# Mutex locks in Go

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func NewAccount(init int) Account
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}
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import "sync"

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}

func NewAccount(init int) Account
    return Account{balance: init}
}

func (a *Account) CheckBalance() int {
    a.lock.Lock()
    defer a.lock.Unlock()
    return a.balance
}
```

# Mutex locks in Go

```
package account

import "sync"

type Account struct {
    balance int
    lock sync.Mutex
}

func NewAccount(init int) Account {
    return Account{balance: init}
}

func (a *Account) CheckBalance() int {
    a.lock.Lock()
    defer a.lock.Unlock()
    return a.balance
}

func (a *Account) Withdraw(v int) {
    a.lock.Lock()
    defer a.lock.Unlock()
    a.balance -= v
}

func (a *Account) Deposit(v int) {
    a.lock.Lock()
    defer a.lock.Unlock()
    a.balance += v
}
```

# Read write locks in Go

```
package account

import "sync"

type Account struct {
    balance int
    lock sync.RWMutex
}

func NewAccount(init int) Account {
    return Account{balance: init}
}

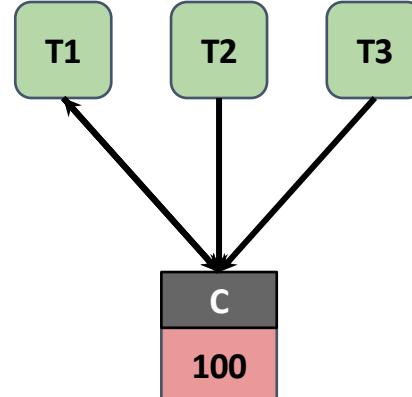
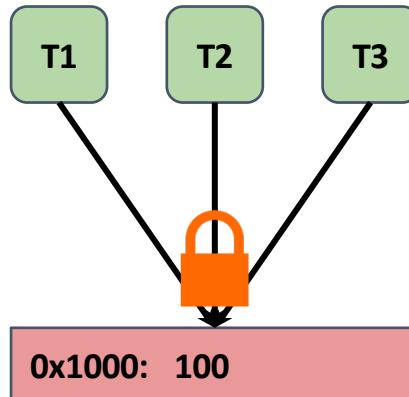
func (a *Account) CheckBalance() int {
    a.lock.RLock()
    defer a.lock.RUnlock()
    return a.balance
}

func (a *Account) Withdraw(v int) {
    a.lock.Lock()
    defer a.lock.Unlock()
    a.balance -= v
}

func (a *Account) Deposit(v int) {
    a.lock.Lock()
    defer a.lock.Unlock()
    a.balance += v
}
```

# Two solutions to the same problem

- Locks:
  - Multiple threads can reference same memory location
  - Use lock to ensure only one thread is updating it at any time
- Channels:
  - Data item initially stored in channel
  - Threads must request item from channel, make updates, and return item to channel



# Go channels

```
// Launch workers
for i := 0; i < numWorkers; i++ {
    go func() {
        // ... do some work
    }()
}
```

- In Go, *channels* and *goroutines* are more idiomatic than locks

# Go channels

```
result := make(chan int, numWorkers)  
  
// Launch workers  
for i := 0; i < numWorkers; i++ {  
    go func() {  
        // ... do some work  
        result <- i  
    }()  
}  
}
```

- In Go, *channels* and *goroutines* are more idiomatic than locks

# Go channels

```
result := make(chan int, numWorkers)

// Launch workers
for i := 0; i < numWorkers; i++ {
    go func() {
        // ... do some work
        result <- i
    }()
}

// Wait until all worker threads have finished
for i := 0; i < numWorkers; i++ {
    handleResult(<-result)
}
fmt.Println("Done!")
```

- In Go, *channels* and *goroutines* are more idiomatic than locks

# Bank account code (using channels)

```
package account

type Account struct {
    // Fill in Here
}

func NewAccount(init int) Account {
    // Fill in Here
}

func (a *Account) CheckBalance() int {
    // What goes Here?
}

func (a *Account) Withdraw(v int) {
    // ???
}

func (a *Account) Deposit(v int) {
    // ???
}
```

# Bank account code (using channels)

```
package account

type Account struct {
    balance chan int
}

func NewAccount(init int) Account {
    a := Account{balance: make(chan int, 1)}
    a.balance <- init
    return a
}

func (a *Account) CheckBalance() int {
    bal := <-a.balance
    a.balance <- bal
    return bal
}

func (a *Account) Withdraw(v int) {
    bal := <-a.balance
    a.balance <- (bal - v)
}

func (a *Account) Deposit(v int) {
    bal := <-a.balance
    a.balance <- (bal + v)
}
```

# select statement in Go

- `select` allows a goroutine to wait on multiple channels at once

```
for {
    select {
        case money := <-dad:
            buySnacks(money)
        case money := <-mom:
            buySnacks(money)
        case default:
            starve()
            time.Sleep(5 * time.Second)
    }
}
```

# Handle timeouts using select

```
result := make(chan int)
timeout := make(chan bool)

// Asynchronously request an
// answer from server, timing
// out after X seconds
askServer(result, timeout)

// Wait on both channels
select {
    case res := <-result:
        handleResult(res)
    case <-timeout:
        fmt.Println("Timeout!")
}

func askServer(
    result chan int,
    timeout chan bool) {

    // Start timer
    go func() {
        time.Sleep(5 * time.Second)
        timeout <- true
    }()

    // Ask server
    go func() {
        response := // ... send RPC
        result <- response
    }()
}
```

# Handle timeouts using select

```
result := make(chan int)
timeout := make(chan bool)

// Asynchronously request an
// answer from server, timing
// out after X seconds
askServer(result, timeout)

// Wait on both channels
select {
    case res := <-result:
        handleResult(res)
    case <-timeout:
        fmt.Println("Timeout!")
}

func askServer(
    result chan int,
    timeout chan bool) {

    // Start timer
    go func() {
        time.Sleep(5 * time.Second)
        timeout <- true
    }()

    // Ask server
    go func() {
        response := // ... send RPC
        result <- response
    }()
}
```