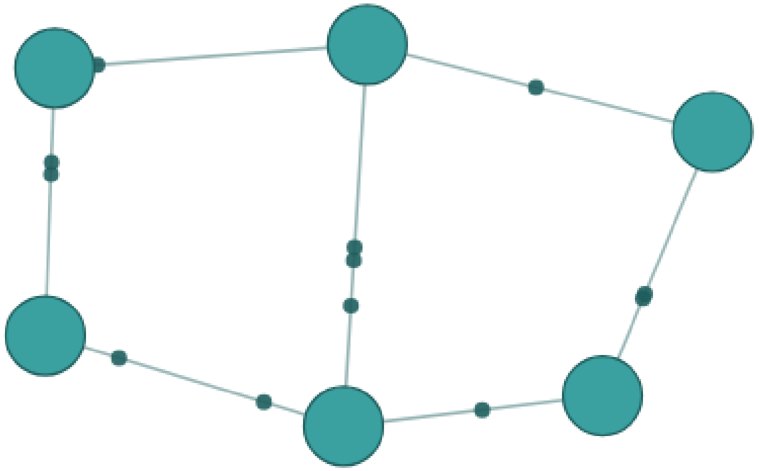
Dancing with Uncertainty

Challenges of Distributed Systems



Grzegorz Piwowarek

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{ 4comprehension.com }

Java Champion | Oracle ACE

WarsawJUG Leader | Vavr Leader

distributed systems · microservices · reactive · java

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CAP Theorem

- **C**onsistency
- **A**vailability
- **P**artition tolerance

Consistency

every read receives the most recent write

(a single-copy illusion)

Availability

every request receives a non-error response

(even if some nodes are down)

Partition tolerance

system continues to operate even if network links are lost

What makes systems...distributed?

distributed systems are systems that communicate over unreliable channels

Network is unreliable

as of 2026

https://slate.com/technology/2014/08/shark-attacks-threaten-google-s-undersea-internet-cables-video.html

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IP over Avian Carriers

Article Talk

In computer networking, **IP over Avian Carriers** (**IPoAC**) is a proposal to carry Internet Protocol (IP) traffic by birds

Risks

An example of packet loss.

https://en.wikipedia.org/wiki/IP_over_Avian_Carriers

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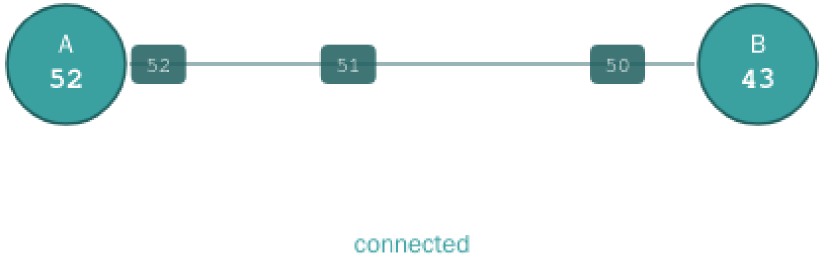
Rule: In the presence of a network partition, a distributed system must choose either *Consistency* or *Availability*.



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The Two Generals Problem

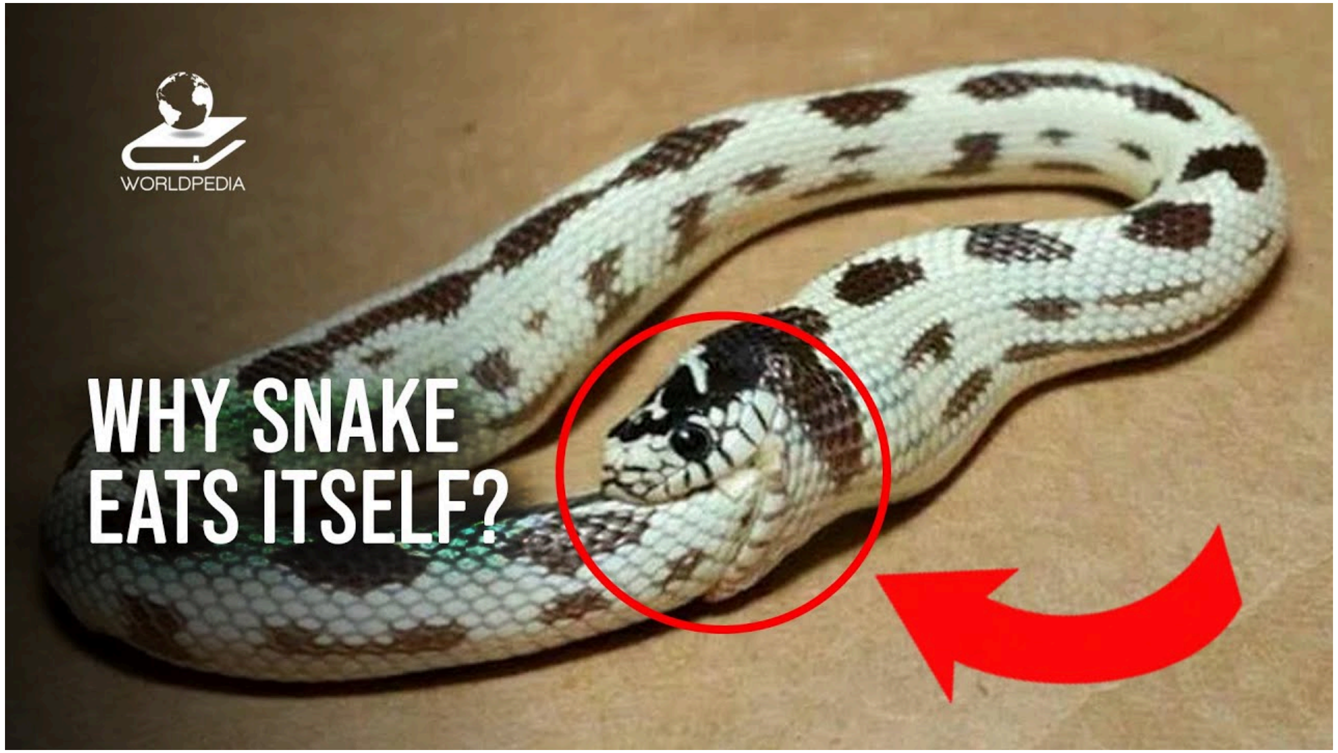
The Scenario

Two generals are planning to attack a city. They can only communicate via messengers, who may be captured.

How can both generals be sure they attack at the same time, given that messages might not arrive?

There is **no deterministic way** for two parties to **coordinate** over an unreliable communication channel.

…


WORLDPEDIA
WHY SNAKE
EATS ITSELF?

https://twitter.com/ddprrt/status/1425418538257428488

https://twitter.com/ddprrt/status/1425418538257428488

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"It was the invention of the null reference in 1965...I call it my billion-dollar mistake."

Tony Hoare

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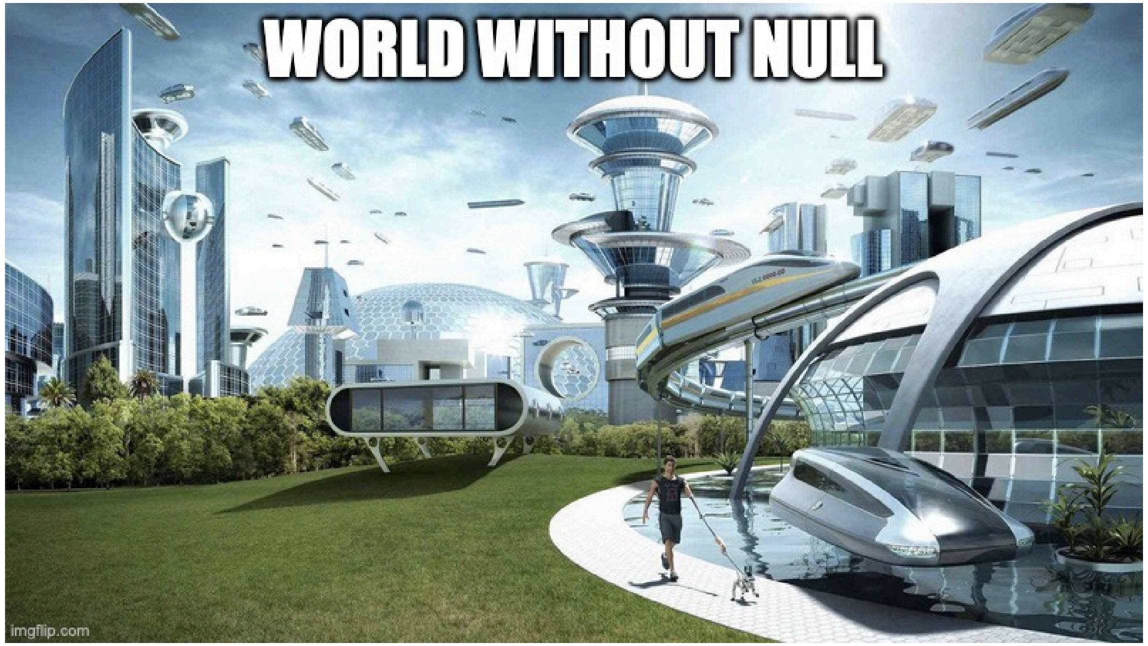

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Another *”billion-dollar mistake”:*

Microservices

Another *”billion-dollar mistake”:*

”Micro”

Microservice vs service?

How small is ”micro”?

N lines of code?

N endpoints?

N classes?

N MBs?

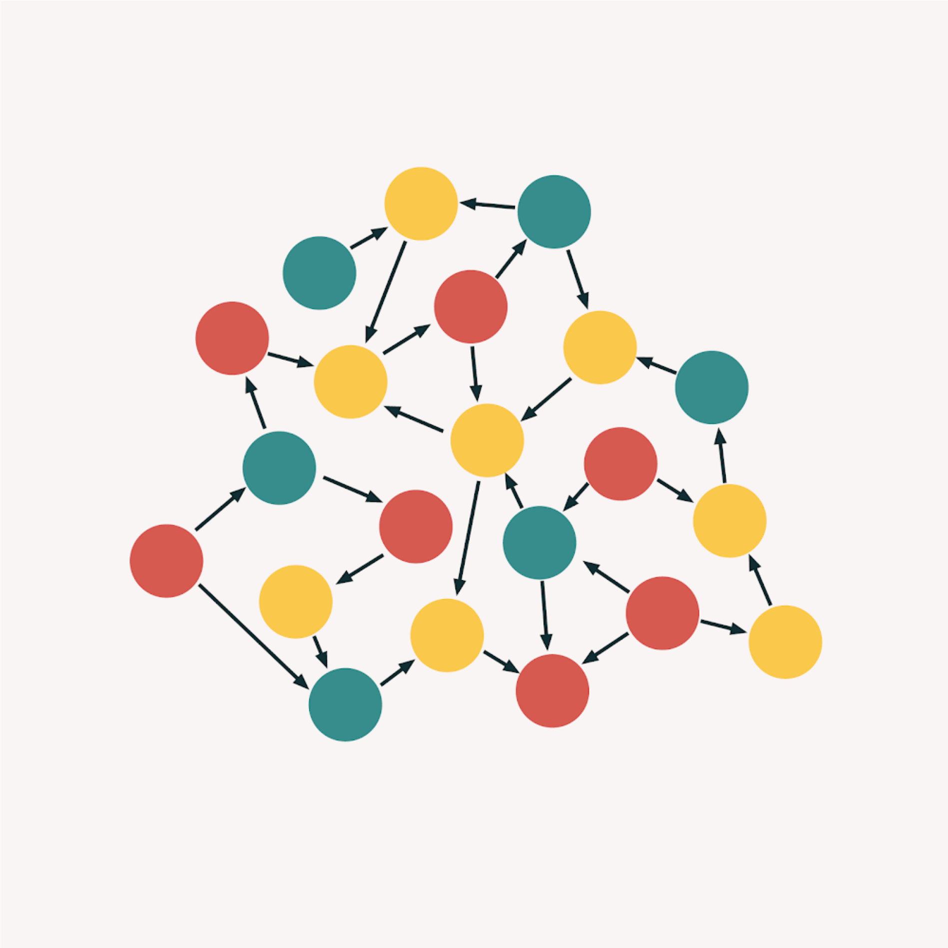
N responsibilities?

Rewritable in X time?

Microservices: the Main Idea

Enable scalability through independence and modularity

Tight coupling - Low cohesion



source: https://enterprisecraftsmanship.com/posts/cohesion-coupling-difference/

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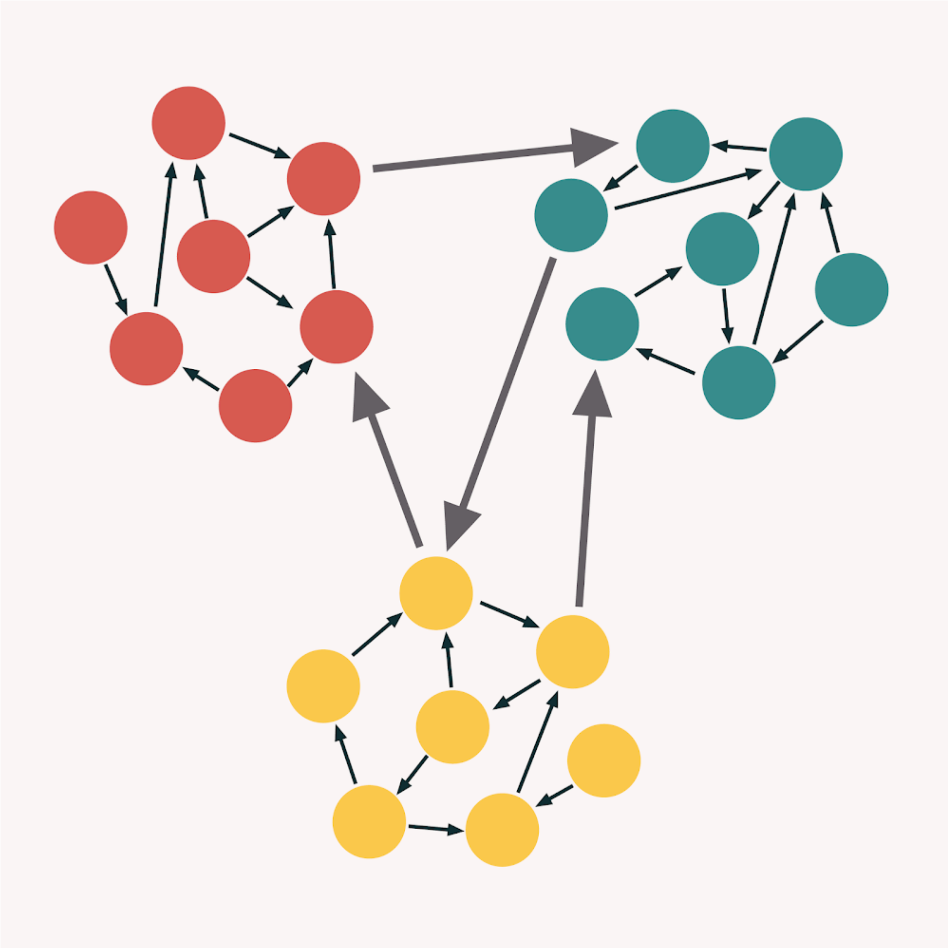
Low coupling - High cohesion



source: https://enterprisecraftsmanship.com/posts/cohesion-coupling-difference/

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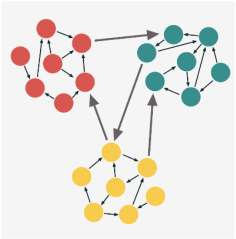
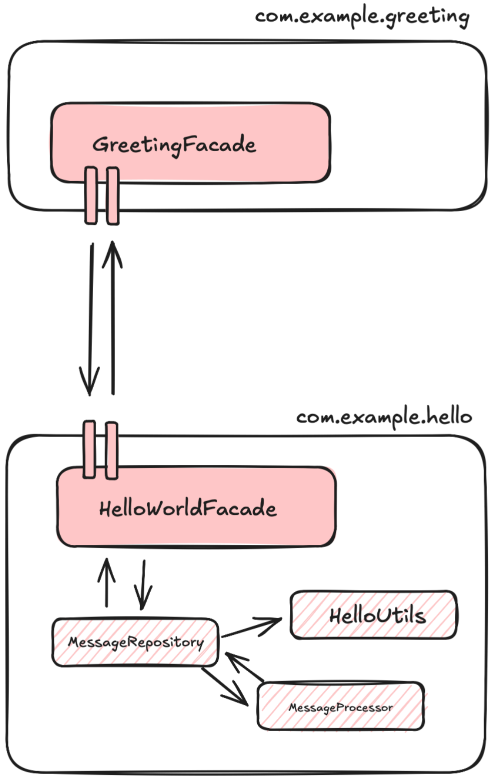
You can have modularity without microservices





Naturally, you don't get all the benefits, but it's not a demanding investment

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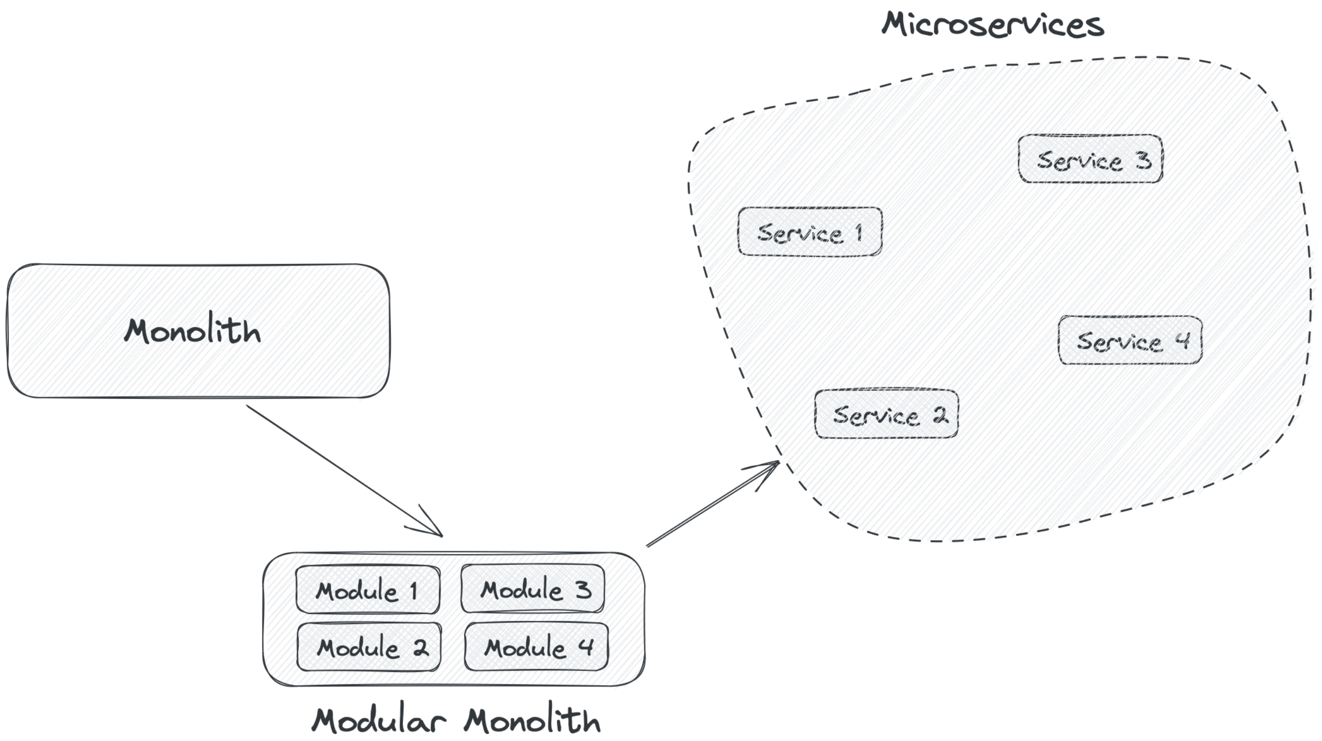
Microservices
Service 3
Service 1
Service 4
Service 2
Monolith
Module 1
Module 3
Module 2
Module 4
Modular Monolith

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"The smaller the service, the more you maximize the benefits and downsides of microservice architecture."

Sam Newman

author: Bruce Wong

Netflix: 2000 engineers

Applying the high scalability tips from Google and Netflix software architectures to your trivial project.

However, don't be fooled by the size of those microservices, because a lot of those so-called microservices at Netflix are a lot larger, just looking at the code base, than the big monoliths that I've worked at, at many other companies.

Paul Bakker

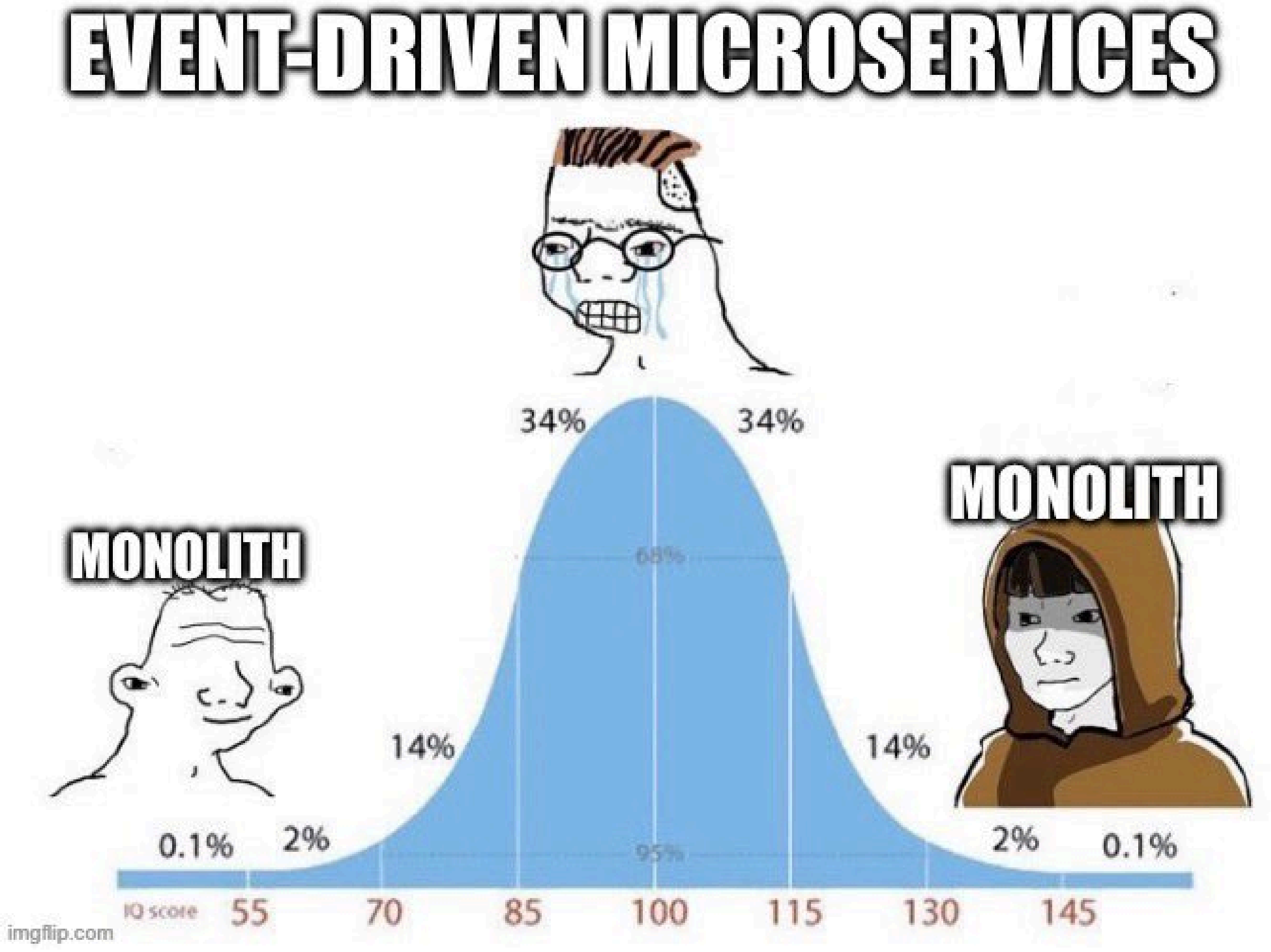
source: https://www.infoq.com/presentations/netflix-java/

Do not ask about the max size, but when to split

So… when do we split?

When it hurts too much

The #1 rule of distributed systems: don’t do it until you have to


EVENT-DRIVEN MICROSERVICES
34%
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115
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145
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The Pragmatic Default


DHH @dhh · Apr 7, 2020

The amount of pain that's been inflicted by the overeager adoption of microservices is immense.

Gergely Orosz @GergelyOrosz · Apr 6, 2020

For the record, at Uber, we're moving many of our microservices to what @copyconstruct calls macroservices (wells-sized services).

Exactly b/c testing and maintaining thousands of microservices is not only hard - it can cause more trouble long-term than it solves the ...

Show more

36 204 826

DHH @dhh

In addition to the Majestic Monolith, someone should write up the pattern of The Citadel: A single Majestic Monolith captures the majority mass of the app, with a few auxiliary outpost apps for highly specialized and divergent needs.

https://twitter.com/dhh/status/1247522358908215296

Our server app is a monolith, one big codebase of several million lines and a few thousand Django endpoints [1], all loaded up and served together. A few services have been split out of the monolith, but we don't have any plans to aggressively break it up.

https://instagram-engineering.com/static-analysis-at-scale-an-instagram-story-8f498ab71a0c

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Reliability in an unreliable world

When sending a message over unreliable channels, how to guarantee delivery?

(...thought experiment...)

Definition

An operation is **idempotent** if performing it multiple times produces the *same effect* as performing it once.

```
f(f(x)) = f(x)
```

Examples

- Setting a user's status to "active" → ✅
- Incrementing a counter → ❌

In a distributed system

Failures and retries are inevitable.

- Network retries may cause duplicate requests
- Clients or load balancers might resend operations
- Idempotency prevents unwanted side effects

Exactly-once delivery?

A fairy tale.

Reality: You only ever get:

- **at-most-once** → messages may be lost
- **at-least-once** → messages may be duplicated

Exactly-once doesn’t exist

- Networks can fail between *send* and *acknowledge*
- Clients can retry
- Servers can crash mid-processing

Exactly-once *effect*

We can't guarantee *exactly-once delivery*,

but we can design for **exactly-once effect** using idempotency.

```
at-least-once delivery + idempotency = exactly-once
```

Resilience Patterns

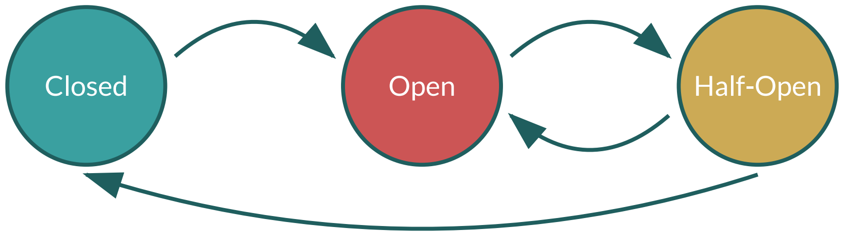
When failures are inevitable, design for graceful degradation.

Circuit Breaker

Prevent cascading failures by **failing fast**.

- **Closed** → requests pass through normally
- **Open** → requests fail immediately (no calls to failing service)
- **Half-Open** → test if service recovered

Circuit Breaker States



Failures trigger opening; timeout triggers half-open; success closes.

Circuit Breaker Example

```java
@CircuitBreaker(name = "paymentService",
                fallbackMethod = "fallbackPayment")
public Payment processPayment(Order order) {
    return paymentClient.charge(order);
}

public Payment fallbackPayment(Order order, Exception e) {
    return Payment.pending(order.id()); // graceful degradation
}
```

Retry with Exponential Backoff

Don't hammer a failing service - back off gradually.

```
Attempt 1: wait 100ms
Attempt 2: wait 200ms
Attempt 3: wait 400ms
Attempt 4: wait 800ms
...
```

Add Jitter

Without jitter, retries synchronize → **thundering herd**.

```
long backoff = (long) Math.pow(2, attempt) * baseDelay;
long jitter = random.nextLong(backoff / 2);
long delay = backoff + jitter;
```

Jitter spreads retries over time, reducing load spikes.

Thundering Herd Problem

When many clients retry at the same time:

- Service just recovered
- All clients retry simultaneously
- Service overwhelmed again
- Cycle repeats

Solution: exponential backoff + jitter

Bulkhead Pattern

Isolate failures to prevent total system collapse.

Named after ship compartments that contain flooding.

Bulkhead Strategies

- **Thread pool isolation** → separate pools per dependency
- **Semaphore isolation** → limit concurrent calls
- **Connection pool limits** → prevent resource exhaustion

```
@Bulkhead(name = "inventoryService",
          type = Bulkhead.Type.THREADPOOL)
public Inventory checkStock(String productId) {
    return inventoryClient.getStock(productId);
}
```

Timeout Strategies

How long should you wait?

It's harder than it looks.

Timeout Considerations

- Too short → false failures, wasted work
- Too long → resource exhaustion, cascading delays
- p99 latency ≠ typical latency
- Downstream timeouts should be shorter than upstream

Timeout Budget

```
Client timeout: 3000ms
  └─ Service A timeout: 2000ms
       └─ Service B timeout: 1000ms
            └─ Database timeout: 500ms
```

Each layer must complete within its budget.

Combining Patterns

```
@CircuitBreaker(name = "backend")
@Bulkhead(name = "backend")
@Retry(name = "backend")
@TimeLimiter(name = "backend")
public CompletableFuture<Result> callBackend() {
    return backendClient.fetch();
}
```

Order matters: Retry → CircuitBreaker → Bulkhead → TimeLimiter

Observability

You can't fix what you can't see.

The Three Pillars

- **Metrics** → aggregated numerical data (counters, gauges, histograms)
- **Logs** → discrete events with context
- **Traces** → request flow across services

You need all three for full visibility.

Distributed Tracing

Follow a request as it travels through multiple services.

Trace Anatomy

```
Trace ID: abc-123
├─ Span: API Gateway (50ms)
│   └─ Span: OrderService (120ms)
│       ├─ Span: InventoryService (45ms)
│       └─ Span: PaymentService (60ms)
│           └─ Span: Database (15ms)
```

Each span represents one unit of work.

Correlation IDs

Propagate a unique ID through all services:

```java
// Incoming request
String traceId = request.getHeader("X-Trace-Id");
if (traceId == null) {
    traceId = UUID.randomUUID().toString();
}
MDC.put("traceId", traceId);

// Outgoing request
httpClient.setHeader("X-Trace-Id", traceId);
```

Now you can correlate logs across all services.

What Tracing Reveals

- Which service is the bottleneck?
- Where did the request fail?
- What's the actual call graph?
- Are there unexpected dependencies?

PACELC Theorem

Daniel Abadi extended CAP to include trade-offs *when no partition occurs*:

If P *(partition) → A or C*
Else *(ok) → Latency or Consistency*

Even without partitions, there’s another trade-off

Waiting for consensus takes time

This is the “ELC” part of PACELC.

Imagine two coffee shops sharing an order system

- **network failure** → choice: *keep taking orders (A)* or *pause until synced (C)*
- **no failure** → each order can be: *fast but maybe outdated (L)* or *slow but always accurate (C)*

Real-world examples

- **Amazon Dynamo / Cassandra** → prioritize *Availability + Low Latency*
- **Google Spanner** → prioritize *Consistency*, accept more latency

temporal coupling

when all your services need to be responsive at the same time

False Dichotomy:

Consistent vs. Inconsistent

Different consistency levels

- **Strong consistency** → Data converges immediately
- **Eventual consistency** → Data converges... eventually
- **Accidental consistency** → Data converges... maybe

All are “consistent” — just in different ways.

Eventual consistency

If no new updates occur, all replicas will ***eventually*** *converge to the same state.*

It’s a trade-off: we get **availability and speed** at the cost of temporary disagreement.

Why this makes sense

- Networks are slow and unreliable
- Waiting for everyone to agree slows everything down
- So we let nodes respond now and sync later

→ **Fast now, consistent later**

Conflict Resolution

When replicas diverge, how do we reconcile?

Last-Write-Wins (LWW)

Simplest approach: highest timestamp wins.

```
Node A: set("key", "A", t=100)
Node B: set("key", "B", t=105)

Result: "B" wins (higher timestamp)
```

Problem: Relies on synchronized clocks. Data can be silently lost.

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Application-Level Resolution

Let the application decide how to merge:

- Shopping cart → union of items
- Counter → sum of increments
- Document → show conflict to user

Requires domain knowledge.

CRDTs

Conflict-free Replicated Data Types

Data structures that **automatically merge** without conflicts.

CRDT Properties

- Replicas can be updated independently
- Updates always converge to the same state
- No coordination required during updates
- Mathematically guaranteed to be conflict-free

CRDT Examples

- **G-Counter** → grow-only counter (each node tracks its own count)
- **PN-Counter** → counter with increments and decrements
- **G-Set** → grow-only set (add-only)
- **OR-Set** → observed-remove set (add and remove)
- **LWW-Register** → last-writer-wins register

G-Counter Example

```
Node A: {A: 5, B: 0, C: 0}  // A incremented 5 times
Node B: {A: 0, B: 3, C: 0}  // B incremented 3 times
Node C: {A: 0, B: 0, C: 2}  // C incremented 2 times

Merge: {A: 5, B: 3, C: 2}   // take max of each
Total: 5 + 3 + 2 = 10
```

No conflicts possible - just take the maximum per node.

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CRDTs in Practice

- **Redis** → CRDT-based active-active replication
- **Riak** → built-in CRDT support
- **Cassandra** → counter columns
- **Collaborative editing** → Google Docs, Figma

CRDT Trade-offs

- ✅ Always available, always convergent
- ✅ No coordination overhead
- ❌ Limited to specific data structures
- ❌ Can grow unbounded (tombstones, version vectors)
- ❌ Eventual consistency only

synchronous communication

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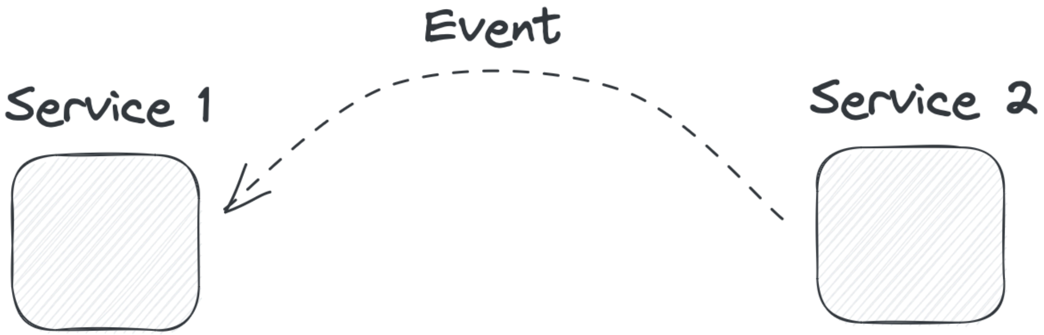
asynchronous communication



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From HTTP calls...

```
OrderService -> PaymentService -> NotificationService
```

Each service calls another directly...

...tight coupling, dependencies, and failure chains.

...to Events

```
OrderService --> publishes OrderCreatedEvent
PaymentService --> consumes OrderCreatedEvent
NotificationService --> consumes PaymentConfirmedEvent
```

Services react to **events** instead of making direct calls.

Local Read Models

Each service maintains its own **local view** of data it needs.

```
@EventListener
void on(PaymentConfirmedEvent event) {
    orderReadModel.updateStatus(event.orderId(), "PAID");
}
```

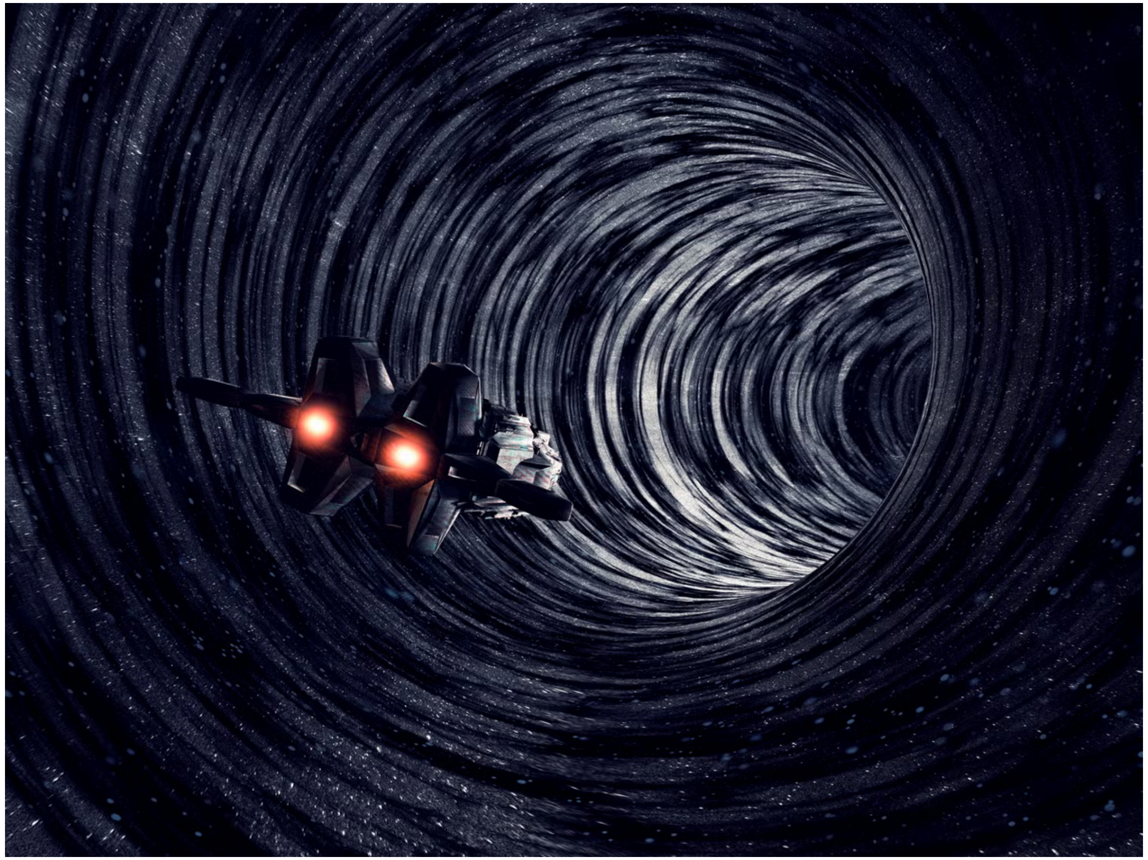
This enables fast, local reads - no cross-service queries needed

...but it eventually consistent

Why Local Read Models?

- No need to call other services for data
- Improves reliability - service can operate even if others are down

Time



13:17:10.431

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```
var first = Instant.now();
var second = Instant.now();
```

first <= second?

Clocks in Distributed Systems

```
Node A
12:30:22.473

Node B
12:30:22.759

Node C
12:30:21.963
```

A **monotonic clock** always moves forward - never backward.

But most `system clocks` are **not monotonic.**

Why clocks go backwards

- **NTP** (Network Time Protocol) adjustment
- Virtual machines paused and resumed
- Leap seconds
- Manual time correction by an admin

Monotonic clocks to the rescue

- In Java: `System.nanoTime()`
- In Linux: `CLOCK_MONOTONIC`

They never go backward, but don't represent "real" time.

In distributed systems, time is… **an illusion**.

The problem with clocks

- Each machine has its own clock
- Clocks drift - even if synced
- Network delays make “now” ambiguous

So: there is no single, global “current time.”

Example

Two servers record an event:

- Server A: event at 12:00:00.100
- Server B: event at 12:00:00.090

Which happened first? 🤔

Why this matters

- Event ordering affects state changes
- Conflicts appear when we can’t tell “what came first”
- Replication, logs, and causality all depend on time

Happened-before relationship

Instead of wall-clock time, we use **causal order**:

$$A \rightarrow B \text{ if } A \text{ happened before } B \text{ (causally)}$$

We care about *ordering* of events, not their timestamps.

Logical clocks

- **Lamport clocks** → simple counters to track causal order
- **Vector clocks** → richer structure to detect concurrent events

They don’t measure real time - they measure **cause and effect**.

Real time vs. logical time

- **Real time** → what your watch shows
- **Logical time** → what the system can *prove* happened first

Distributed systems live in **logical time**.

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Google's Spanner uses special hardware clocks (TrueTime API) ⏱️

But even then, they include an **uncertainty window** - because perfect time doesn't exist.

Summary

- Each node has its own imperfect sense of time
- We can't rely on timestamps for ordering
- We use **logical or causal time** to reason safely

Time is relative - especially in distributed systems 🌌

Consensus & Coordination

Getting distributed nodes to agree on something.

Leader Election

Many distributed systems need a single leader:

- Database primary replica
- Distributed lock manager
- Kafka partition leader
- Scheduler coordination

Why Leader Election Is Hard

- Network partitions → multiple nodes think they're leader
- Clock skew → lease expiration disagreements
- Process pauses → GC, VM migrations
- Failures during election → stuck state

Consensus Algorithms

- **Paxos** → the original (and notoriously hard to understand)
- **Raft** → designed for understandability
- **Zab** → ZooKeeper's protocol

All solve the same fundamental problem: agreement despite failures.

Raft in a Nutshell

1. Nodes start as **followers**
2. If no heartbeat from leader → become **candidate**
3. Request votes from other nodes
4. Majority votes → become **leader**
5. Leader replicates log entries to followers

Practical Leader Election

Don't implement consensus yourself. Use:

- **ZooKeeper** → battle-tested, ephemeral nodes
- **etcd** → Kubernetes' choice, Raft-based
- **Consul** → service mesh + KV store

Distributed Locking

Mutual exclusion across multiple nodes.

Spoiler: it's **really hard** to get right.

The Redlock Controversy

Redis proposed Redlock algorithm for distributed locks.

Martin Kleppmann (DDIA author) argued it's **unsafe**.

- Clock assumptions are unrealistic
- Process pauses can violate safety
- GC can cause lock to expire while holding it

Fencing Tokens

Safer approach: use monotonically increasing tokens.

```
Lock acquired with token: 42

// Later, when using the lock:
storage.write(data, fencingToken=42)

// Storage rejects writes with old tokens
if (requestToken < currentToken) reject();
```

The resource itself validates the lock.

When You Need Distributed Locks

- **Efficiency** → prevent duplicate work (lock loss is OK)
- **Correctness** → prevent data corruption (lock loss is NOT OK)

For correctness, use proper consensus (ZooKeeper, etcd) or fencing tokens.

Split Brain Problem

When network partition creates two groups, each thinking they're the authority.

Split Brain Scenario

```
      [Network Partition]
            |         |
+----------+      +----------+
| Node A   |      | Node C   |
| Node B   |      | Node D   |
+----------+      +----------+
"We're the       "We're the
 cluster!"        cluster!"
```

Both sides accept writes → data divergence.

Preventing Split Brain

- **Quorum** → require majority (N/2 + 1) for decisions
- **STONITH** → "Shoot The Other Node In The Head" (force restart)
- **Fencing** → isolate the minority partition
- **Witness node** → odd number of voters

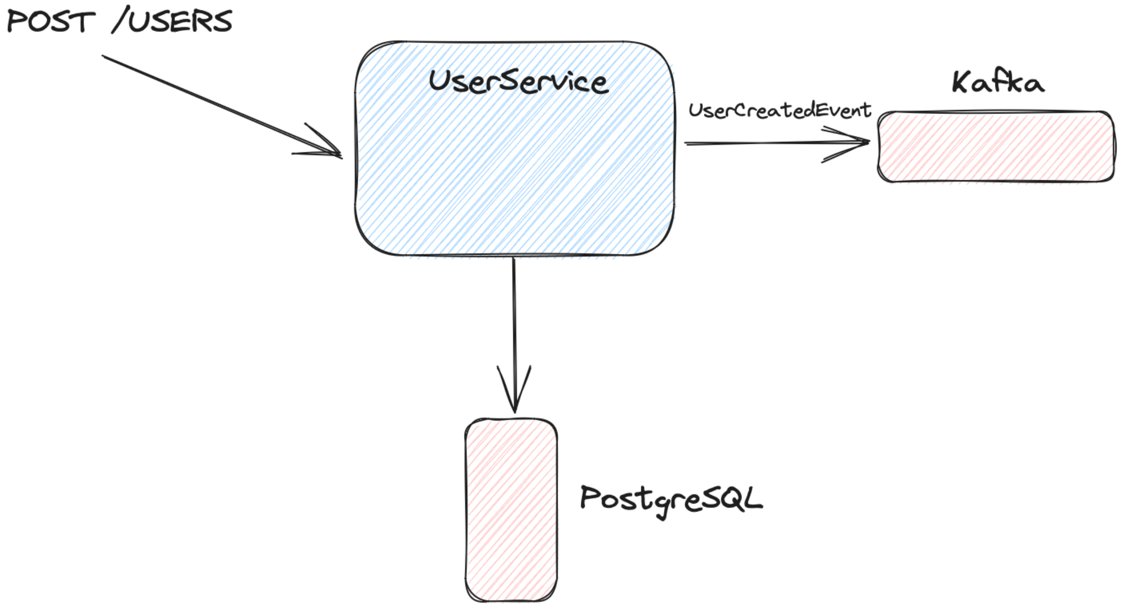
Quorum Math

```
3 nodes: need 2 to agree (can lose 1)
5 nodes: need 3 to agree (can lose 2)
7 nodes: need 4 to agree (can lose 3)
```

Only one partition can ever have a majority.

This is why ZooKeeper/etcd recommend odd numbers.

Eventual Consistency != Accidental Consistency


POST /USERS
UserService
UserCreatedEvent
Kafka
PostgreSQL

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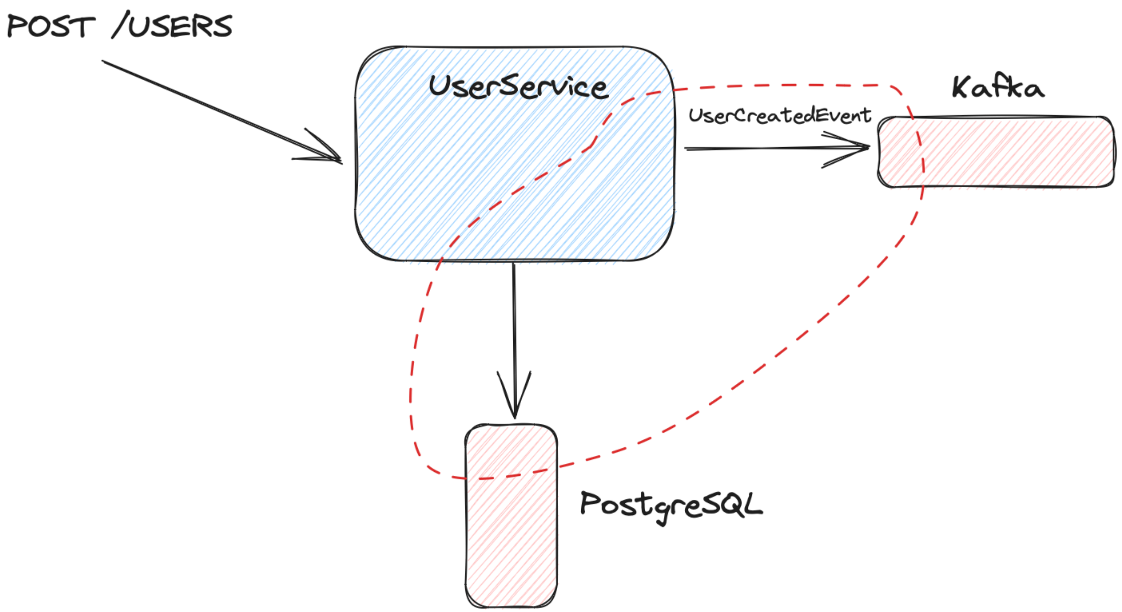
POST /USERS
UserService
UserCreatedEvent
Kafka
PostgreSQL

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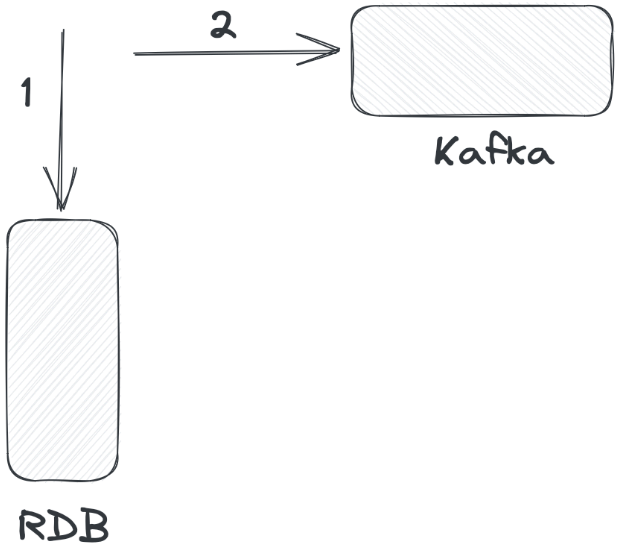
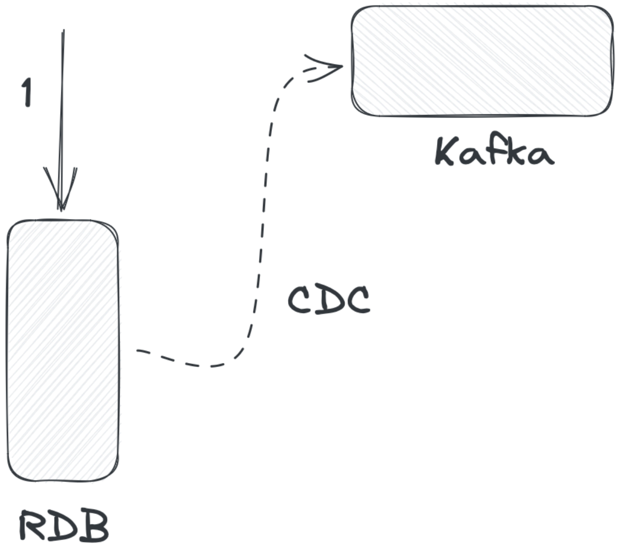
```java
@Transactional
public void createUser(CreateUserCommand command) {
    var user = from(command);

    persist(user);                          // 1
    send(UserCreatedEvent.from(user)); // 2
}
```

`@Transactional` won't save you in the distributed world

Dual-Write (distributed transaction)



Single-Write with async propagation



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Transactional Outbox Pattern

Change Data Capture

Transactional Outbox Pattern

Write the event to a local **outbox table** as part of the same transaction.

```
@Transactional
public void createOrder(Order order) {
    orderRepository.save(order);
    outboxRepository.save(new OutboxEvent("OrderCreated", order.i
}
```

Then a separate process reads the outbox and publishes the events

Trivial Publisher

```
while (true) {
    for (OutboxEvent event : outboxRepository.findUnpublished())
        eventBus.publish(event.toDomainEvent());
        event.markAsPublished();
    }
}
```

Reliable, asynchronous, and decoupled event publishing.

Change Data Capture (CDC)

Instead of polling the outbox table manually...

We can let the database **stream its own changes**.

CDC in Action

- Tools like **Debezium** rely on db replication protocols
- Each committed change becomes an event
- No need to modify application logic

```
-- Database change -->
INSERT INTO outbox (...) VALUES (...)

-- Debezium -->
Produces Kafka event: OrderCreated { orderId: 42 }
```

Outbox + CDC Combo

Most robust solution:

- Use the **outbox table** for atomic writes
- Use **CDC** to stream events out automatically
- No dual writes, no lost events, no external transactions

Trade-offs

- Increased complexity (extra tables/processes)
- Possible duplication → requires idempotency

Distributed Transactions

When one business operation spans multiple services or databases.

- Each service has its own local data and transaction boundaries.
- We still want **atomicity** across them.

But... there's no global transaction manager in distributed systems.

Example

Booking a trip:

- Reserve a flight ✈️
- Book a hotel 🏨
- Charge a credit card 💳

If one step fails, the others must be reverted.

Two-Phase Commit (2PC)

Classic protocol to coordinate distributed commits.

1. **Prepare phase** - coordinator asks all participants if they can commit.
2. **Commit phase** - if all say “yes”, everyone commits; otherwise, all roll back.

2PC Pros and Cons

- ✅ Guarantees atomicity across systems.
- ❌ Introduces a single point of failure – the coordinator.
- ❌ Participants must lock data until the commit is decided.
- ❌ Doesn’t scale well under high latency or partial failures.

When 2PC Fails

If the coordinator crashes between phases...

- Some participants may have committed.
- Others may still be waiting.
- System enters an **uncertain state**.

Recovery requires manual intervention or a timeout heuristic.

The Saga Pattern

An alternative to distributed transactions.

- Each step is a **local transaction**.
- On failure, execute **compensating actions.**

Two Saga Coordination Styles

- **Choreography** - services react to each other's events.
- **Orchestration** - a central orchestrator tells each participant what to do.

Both achieve eventual consistency, but with different trade-offs.

Saga Example

```
BookTripSaga:
  1. FlightService.reserve(flight)
  2. HotelService.book(hotel)
  3. PaymentService.charge(user)

If step 3 fails:
  -> HotelService.cancelBooking()
  -> FlightService.releaseSeat()
```

Transaction Isolation

Even inside a single database, transactions can interfere with each other.

Isolation defines **how visible** one transaction's changes are to others.

Remember PACELC?

ACID Refresher

- **A**tomicity - all or nothing
- **C**onsistency - valid state transitions
- **I**solation - no interference
- **D**urability - once committed, it stays

Why Isolation Matters

Concurrent transactions may cause anomalies:

- **Dirty Read** - see uncommitted data
- **Non-repeatable Read** - unexpected data changes
- **Phantom Read** - new rows appear unexpectedly
- **Lost Update** - two transactions overwrite each other

Dirty Read Example

```
T1: UPDATE accounts SET balance = balance - 100 WHERE id=1;
T2: SELECT balance FROM accounts WHERE id=1; -- sees uncommitted
T1: ROLLBACK;
```

T2 read something that never really existed.

Non-Repeatable Read Example

```
T1: SELECT * FROM orders WHERE id = 1; -- sees "status = NEW"
T2: UPDATE orders SET status = 'PAID' WHERE id = 1; COMMIT;
T1: SELECT * FROM orders WHERE id = 1; -- sees "status = PAID"
```

Same query, different result - during one transaction.

Phantom Read Example

```sql
T1: SELECT * FROM orders WHERE status = 'NEW'; -- returns 3 rows
T2: INSERT INTO orders (status) VALUES ('NEW'); COMMIT;
T1: SELECT * FROM orders WHERE status = 'NEW'; -- now 4 rows
```

New “phantom” data appears mid-transaction.

Write Skew Anomaly

Occurs when two concurrent transactions read overlapping data and make **non-conflicting writes** based on those reads.

Even though each transaction is consistent on its own, the *combined result* breaks an invariant.

Classic Example

Hospital rule: **at least one doctor must be on call.**

```
CREATE TABLE doctors (
    id INT,
    on_call BOOLEAN
);
-- Initially:
-- Dr. Alice: on_call = true
-- Dr. Bob:   on_call = true
```

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Step 1 - Two Transactions Start

```
T1: SELECT * FROM doctors WHERE on_call = true;
-- sees Alice + Bob

T2: SELECT * FROM doctors WHERE on_call = true;
-- sees Alice + Bob
```

Both see that someone else is on call.

Step 2 - Both Decide to Go Off Call

```
T1: UPDATE doctors SET on_call = false WHERE name = 'Alice';
T2: UPDATE doctors SET on_call = false WHERE name = 'Bob';
```

Each assumes the other doctor stays on call.

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Step 3 - Both Commit

```
T1: COMMIT;
T2: COMMIT;
```

Invariant broken: nobody is on call anymore 🚨

Why It Happens

- Both transactions read the same initial state
- Each makes a decision that was valid at that moment
- No direct conflict → no locking → no blocking
- Combined result violates a business rule

Isolation Levels and Write Skew

Isolation Level	Prevents Write Skew?
Read Committed	❌
Repeatable Read	❌ (in most DBs)
Serializable	✅

Only Serializable prevents it, e.g. via predicate locks or SSI (Serializable Snapshot Isolation).

Serializable ≠ Simple

Serializable isolation **simulates sequential execution**.

But it comes at a cost:

- Higher contention and locking
- Deadlocks
- Lower throughput

Data Partitioning

When one database isn't enough.

Sharding Strategies

- **Range-based** → partition by key ranges (A-M, N-Z)
- **Hash-based** → hash(key) mod N
- **Directory-based** → lookup table maps keys to shards

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Range-Based Sharding

```
Shard 1: users A-F
Shard 2: users G-M
Shard 3: users N-S
Shard 4: users T-Z
```

- ✅ Range queries are efficient
- ❌ Hot spots if data isn't uniform ("Smith" problem)

Hash-Based Sharding

```
shard = hash(userId) % numShards

hash("alice") % 4 = 2  → Shard 2
hash("bob")   % 4 = 0  → Shard 0
hash("carol") % 4 = 2  → Shard 2
```

- ✅ Even distribution
- ❌ Range queries require scatter-gather
- ❌ Adding shards = rehash everything

Consistent Hashing

Minimize data movement when adding/removing nodes.

```
Ring: 0 ────────────────────────── 2^32
        |     |           |     |
     Node A   Key1     Node B   Key2
```

Keys move to the next node on the ring.

Adding a node only affects its neighbors.

Rebalancing

What happens when you add or remove nodes?

Rebalancing Challenges

- Data must move between nodes
- System should remain available during rebalancing
- Rebalancing consumes network and disk I/O
- Hot spots can form during migration

Rebalancing Strategies

- **Fixed partitions** → more partitions than nodes, just reassign
- **Dynamic partitioning** → split/merge partitions as needed
- **Proportional partitioning** → partitions per node scales with data

Kafka, Cassandra, MongoDB each have different approaches.

Cross-Shard Queries

The hardest problem in sharding:

```
SELECT * FROM orders
WHERE user_id = 123
AND product_category = 'electronics'
```

If sharded by user_id, category queries hit all shards.

Solution: denormalize, or use secondary indexes.

API Evolution

How to change APIs without breaking consumers.

The Challenge

- Multiple services with independent deployment
- Can't update all consumers simultaneously
- Old and new versions must coexist

Versioning Strategies

- **URL versioning** → /api/v1/users, /api/v2/users
- **Header versioning** → Accept: application/vnd.api.v2+json
- **Query parameter** → /api/users?version=2

Each has trade-offs in discoverability and complexity.

Backward Compatibility

New version can read old data:

```
// Old format
{ "name": "Alice" }

// New code handles both
String fullName = json.has("fullName")
    ? json.getString("fullName")
    : json.getString("name");   // fallback
```

Forward Compatibility

Old version can read new data:

```
// New format with extra field
{ "name": "Alice", "middleName": "Marie" }

// Old code ignores unknown fields
@JsonIgnoreProperties(ignoreUnknown = true)
public class User {
    private String name;
}
```

Schema Evolution

Binary formats with built-in compatibility:

- **Avro** → schema registry, reader/writer schemas
- **Protocol Buffers** → field numbers, optional fields
- **Thrift** → similar to Protobuf

Protobuf Evolution Rules

```
message User {
  string name = 1;
  // int32 age = 2;         // removed - don't reuse!
  string email = 3;         // added - new field number
  optional string phone = 4; // optional for compatibility
}
```

- Never change field numbers
- Never reuse deleted field numbers
- Add fields as optional or with defaults

Consumer-Driven Contracts

Let consumers define what they need:

- Consumers write contract tests
- Provider verifies contracts before release
- Tools: Pact, Spring Cloud Contract

Prevents accidental breaking changes.

Using common sense is the ultimate Best Practice™.

Thank You!

Need help? Reach out! It's free.

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