Distributed Databases

Instructor: Matei Zaharia

cs245.stanford.edu

Outline

Review: Atomic Commitment

Informally: either all participants commit a transaction, or none do

“participants” = partitions involved in a given transaction

Two Phase Commit (2PC)

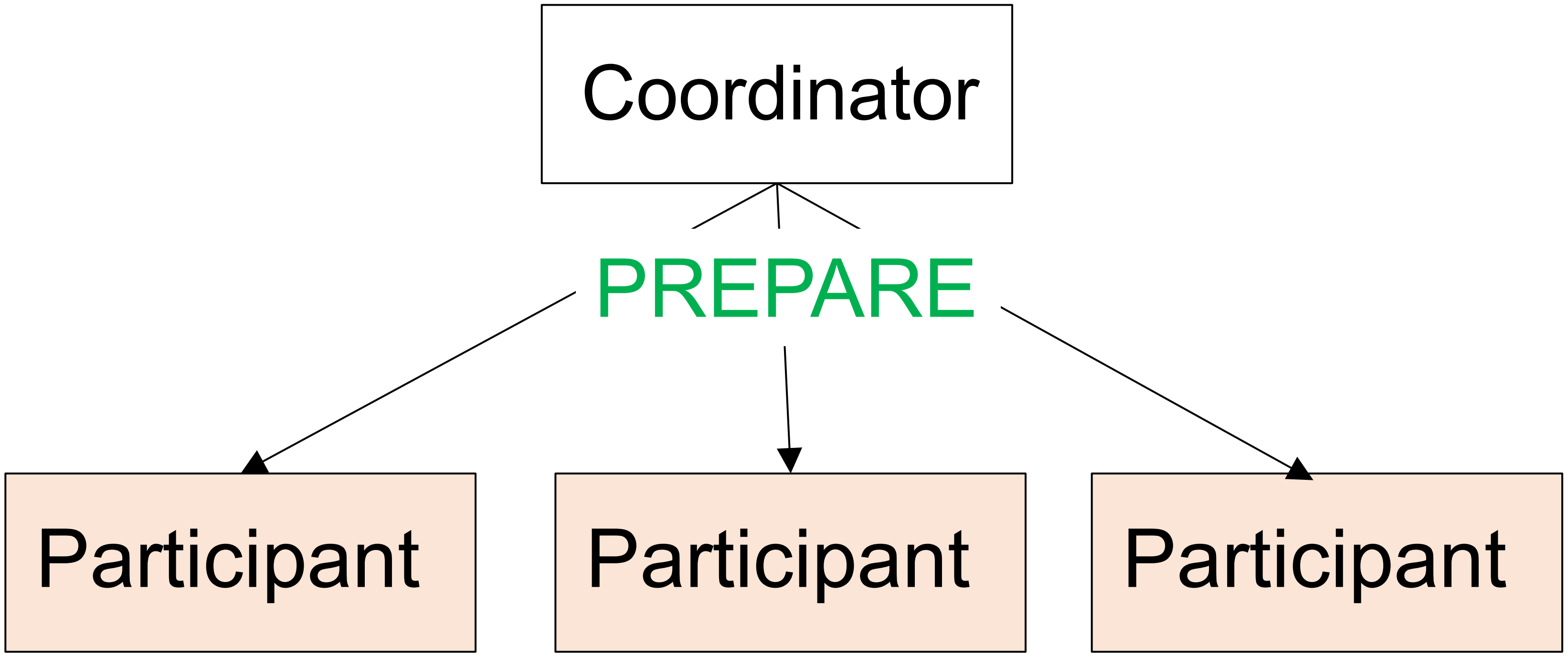
1. Transaction coordinator sends *prepare* message to each participating node

2. Each participating node responds to coordinator with *prepared* or *no*

3. If coordinator receives all *prepared*:
   - » Broadcast *commit*

4. If coordinator receives any *no:*
   - » Broadcast *abort*

What Could Go Wrong?



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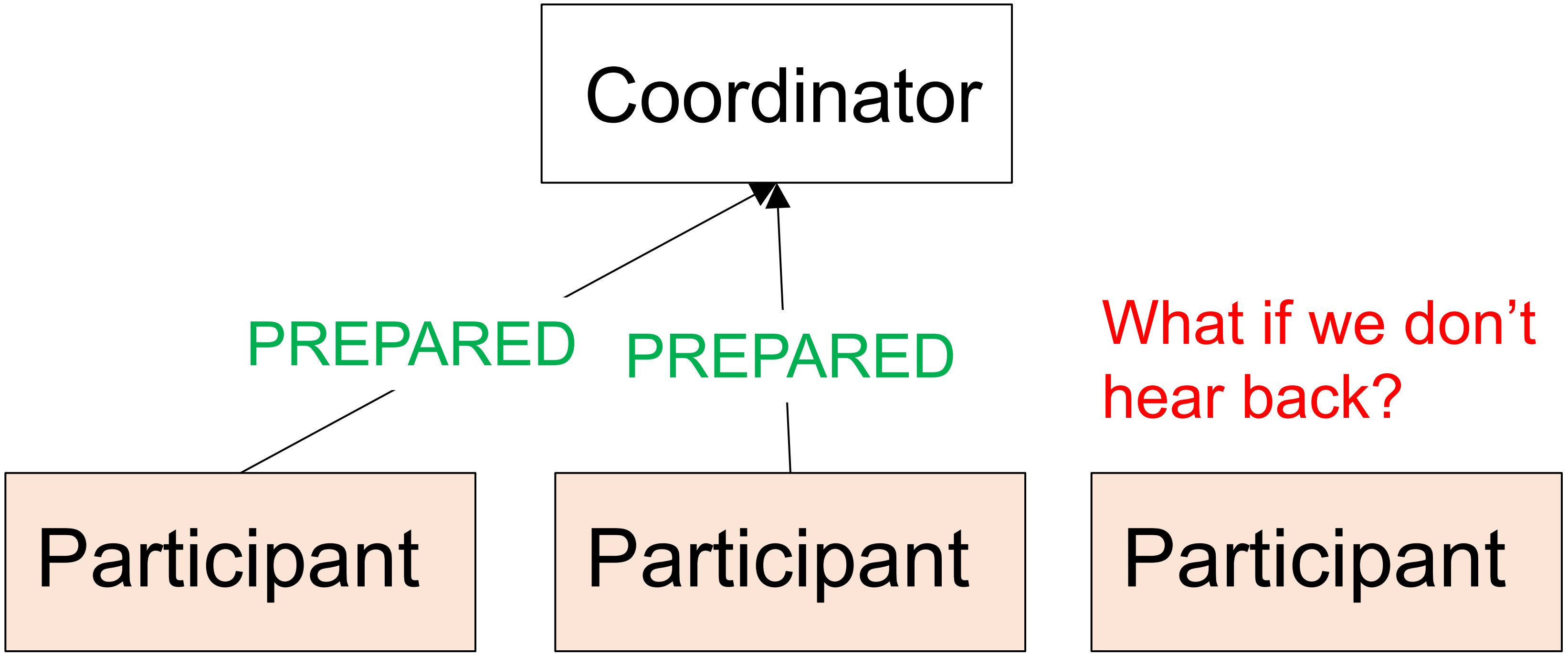


Case 1: Participant Unavailable

We don’t hear back from a participant

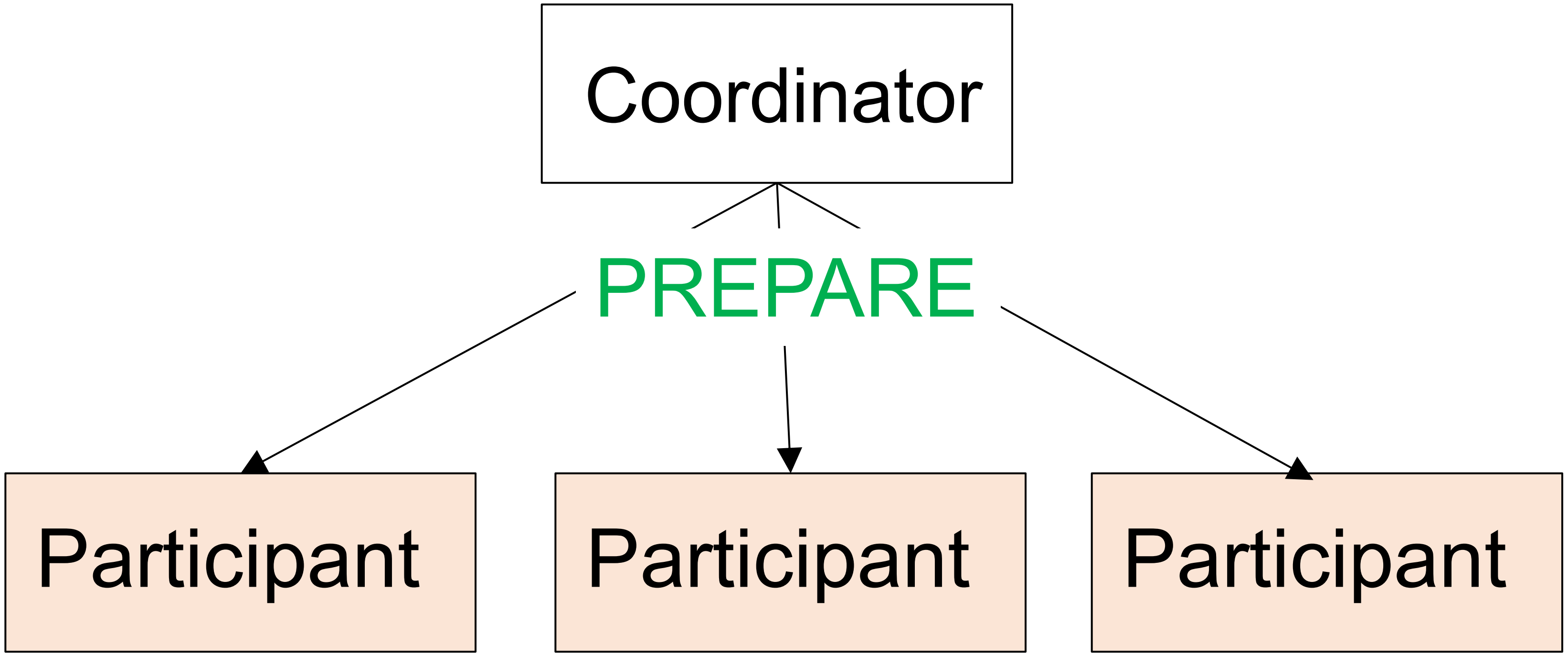
Coordinator can still decide to *abort*

» Coordinator makes the final call!

Participant comes back online?

» Will receive the *abort* message

What Could Go Wrong?



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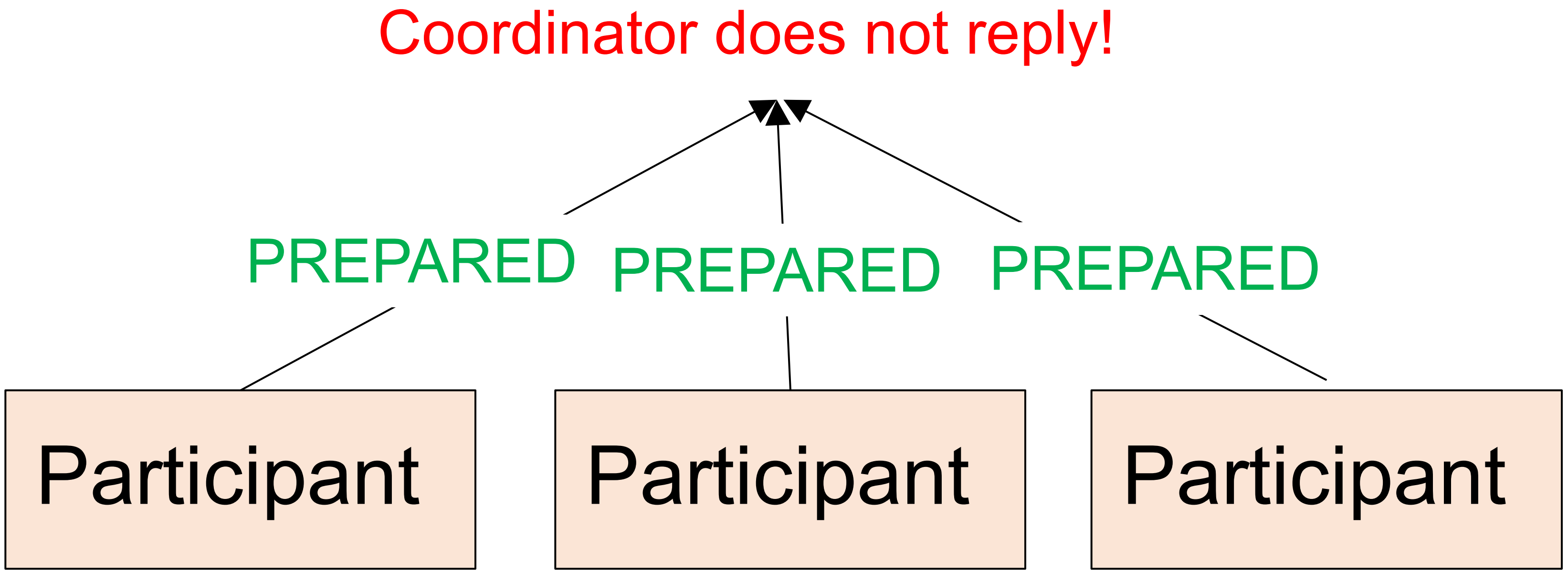


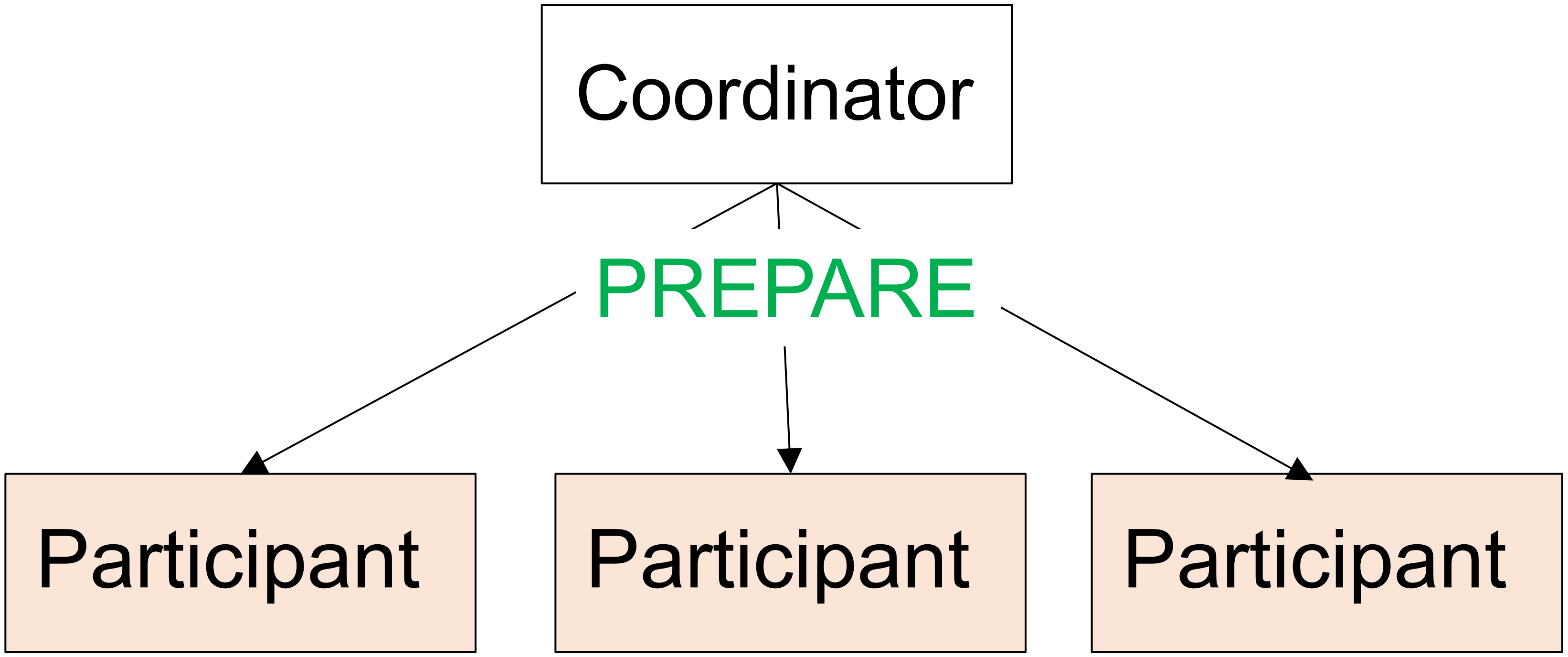
Case 2: Coordinator Unavailable

Participants cannot make progress

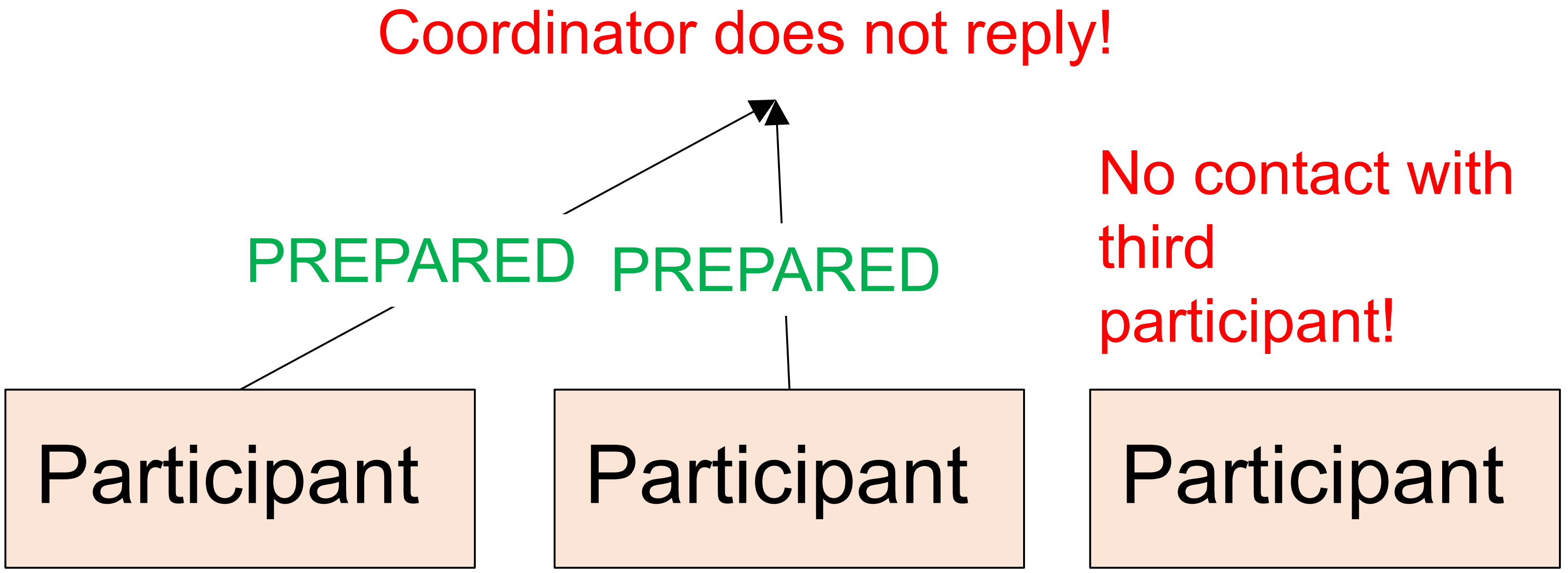
But: can agree to elect a *new* coordinator, never listen to the old one (using consensus)

- » Old coordinator comes back? Overruled by participants, who reject its messages

What Could Go Wrong?



What Could Go Wrong?


Coordinator does not reply!
PREPARED
PREPARED
No contact with third participant!
Participant
Participant
Participant

Case 3: Coordinator and Participant Unavailable

Worst-case scenario:

- » Unavailable/unreachable participant voted to *prepare*
- » Coordinator heard back all *prepare*, started to broadcast *commit*
- » Unavailable/unreachable participant *commits*

Rest of participants *must* wait!!!

Other Applications of 2PC

The “participants” can be any entities with distinct failure modes; for example:

- » Add a new user to database and queue a request to validate their email
- » Book a flight from SFO -> JFK on United and a flight from JFK -> LON on British Airways
- » Check whether Bob is in town, cancel my hotel room, and ask Bob to stay at his place

Coordination is Bad News

Every atomic commitment protocol is *blocking* (i.e., may stall) in the presence of:

- » Asynchronous network behavior (e.g., unbounded delays)
  - Cannot distinguish between delay and failure
- » Failing nodes
  - If nodes never failed, could just wait

Cool: actual theorem!

Outline

Replication strategies

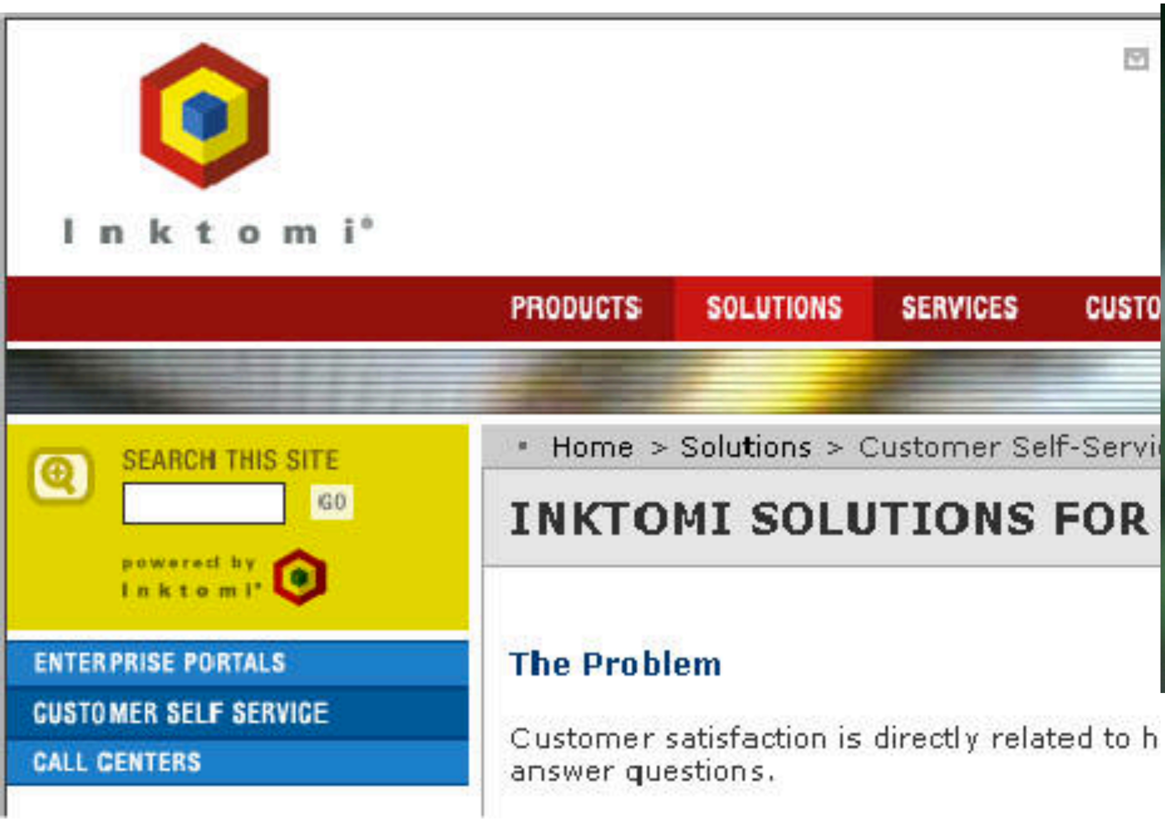
Partitioning strategies

Atomic commitment & 2PC

CAP

Avoiding coordination

Parallel processing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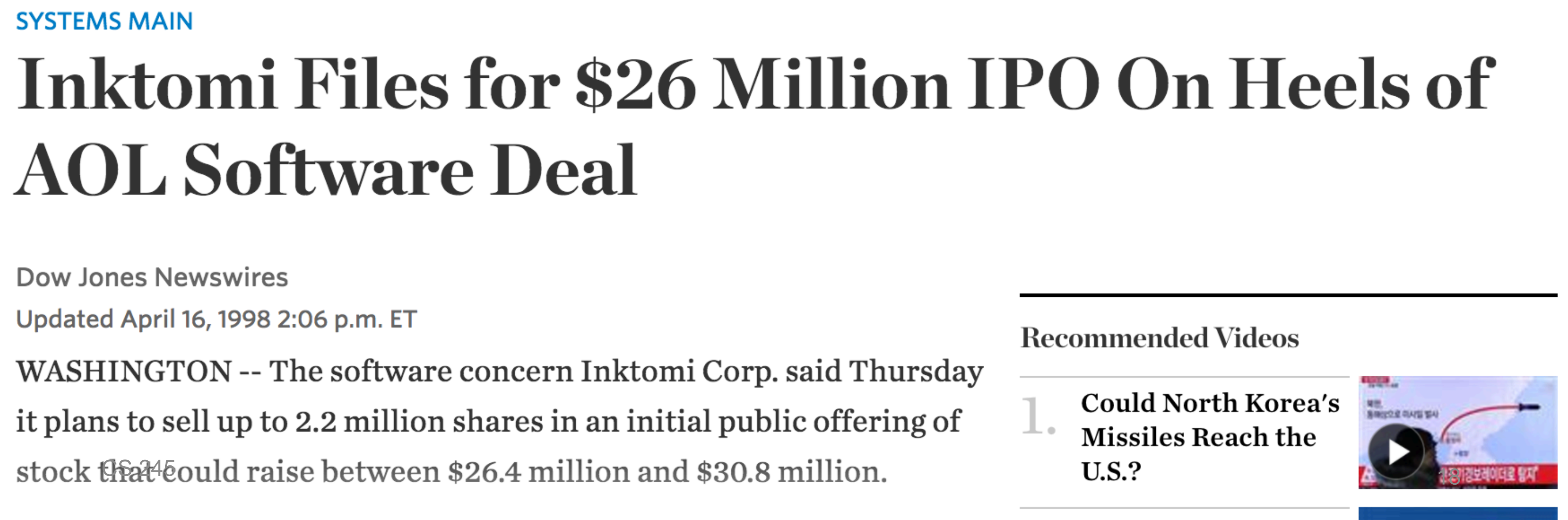
The Problem

Customer satisfaction is directly related to h
answer questions.

Eric Brewer


SYSTEMS MAIN

Inktomi Files for $26 Million IPO On Heels of AOL Software Deal

Dow Jones Newswires

Updated April 16, 1998 2:06 p.m. ET

WASHINGTON -- The software concern Inktomi Corp. said Thursday it plans to sell up to 2.2 million shares in an initial public offering of stock that could raise between $26.4 million and $30.8 million.

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Asynchronous Network Model

Messages can be arbitrarily delayed

Can’t distinguish between delayed messages and failed nodes in a finite amount of time

CAP Theorem

In an asynchronous network, a distributed database can either:

- » guarantee a response from any replica in a finite amount of time (“availability”) **OR**
- » guarantee arbitrary “consistency” criteria/constraints about data

but not both

CAP Theorem

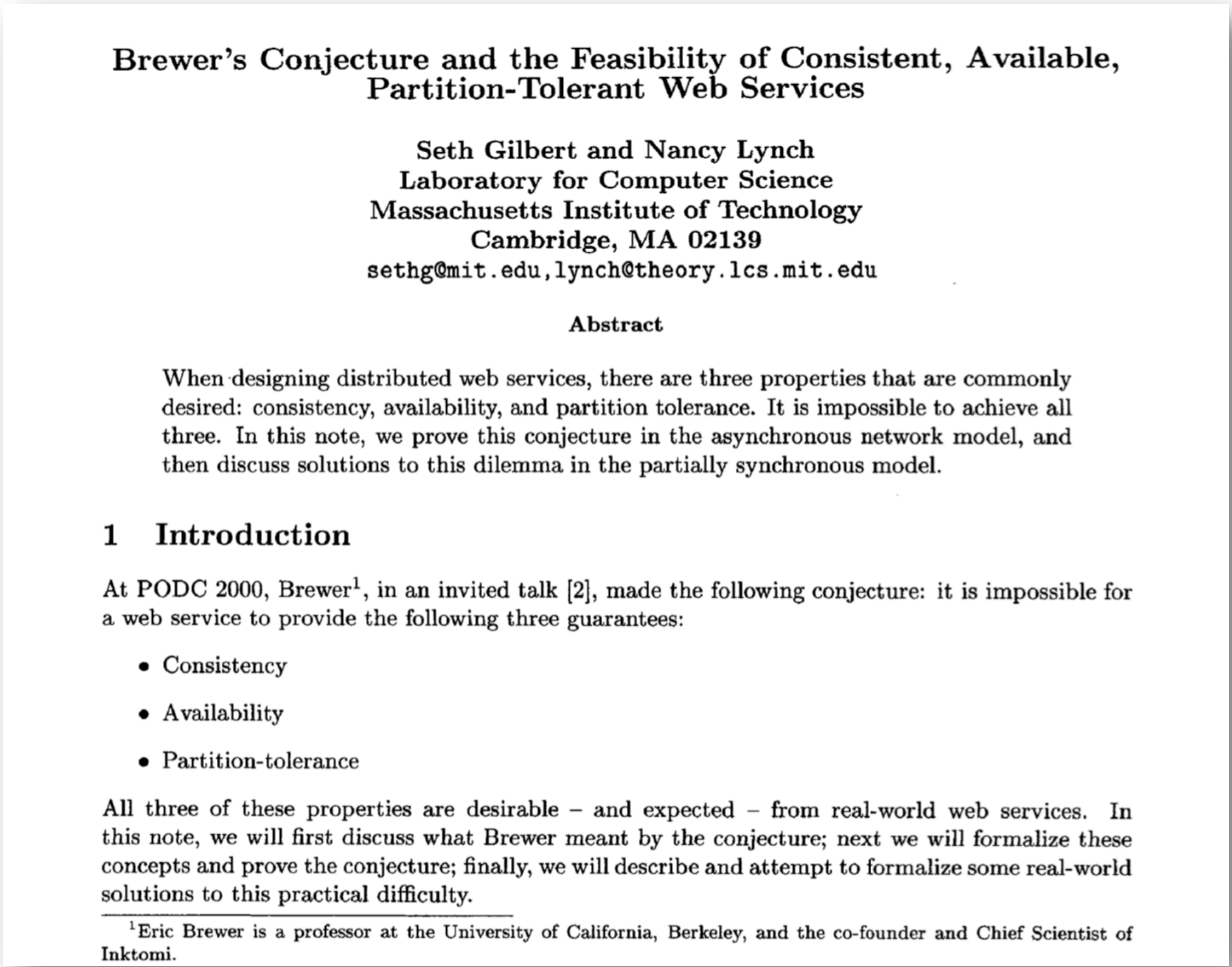
Choose either:

- » Consistency and “Partition tolerance” (CP)
- » Availability and “Partition tolerance” (AP)

Example consistency criteria:

- » Exactly one key can have value “Matei”

CAP is a reminder: no free lunch for distributed systems



Brewer's Conjecture and the Feasibility of Consistent, Available, Partition-Tolerant Web Services

Seth Gilbert and Nancy Lynch
Laboratory for Computer Science
Massachusetts Institute of Technology
Cambridge, MA 02139
`sethg@mit.edu,lynch@theory.lcs.mit.edu`

Abstract

When designing distributed web services, there are three properties that are commonly desired: consistency, availability, and partition tolerance. It is impossible to achieve all three. In this note, we prove this conjecture in the asynchronous network model, and then discuss solutions to this dilemma in the partially synchronous model.

1 Introduction

At PODC 2000, Brewer[1], in an invited talk [2], made the following conjecture: it is impossible for a web service to provide the following three guarantees:

- Consistency
- Availability
- Partition-tolerance

All three of these properties are desirable – and expected – from real-world web services. In this note, we will first discuss what Brewer meant by the conjecture; next we will formalize these concepts and prove the conjecture; finally, we will describe and attempt to formalize some real-world solutions to this practical difficulty.

[1]Eric Brewer is a professor at the University of California, Berkeley, and the co-founder and Chief Scientist of Inktomi.

Why CAP is Important

Reminds us that “consistency” (serializability, various integrity constraints) is expensive!

- » Costs us the ability to provide “always on” operation (availability)
- » Requires expensive coordination (synchronous communication) even when we don’t have failures

Let’s Talk About Coordination

If we’re “AP”, then we don’t have to talk even when we can!

If we’re “CP”, then we have to talk all the time

How fast can we send messages?

Let’s Talk About Coordination

If we’re “AP”, then we don’t have to talk even when we can!

If we’re “CP”, then we have to talk all the time

How fast can we send messages?

- » Planet Earth: 144ms RTT
    - (77ms if we drill through center of earth)
- » Einstein!

Multi-Datacenter Transactions

Message delays often much worse than speed of light (due to routing)

44ms apart? maximum 22 conflicting transactions per second

- » Of course, no conflicts, no problem!
- » Can scale out across many keys, etc

Pain point for many systems

Do We Have to Coordinate?

Is it possible achieve some forms of "correctness" without coordination?

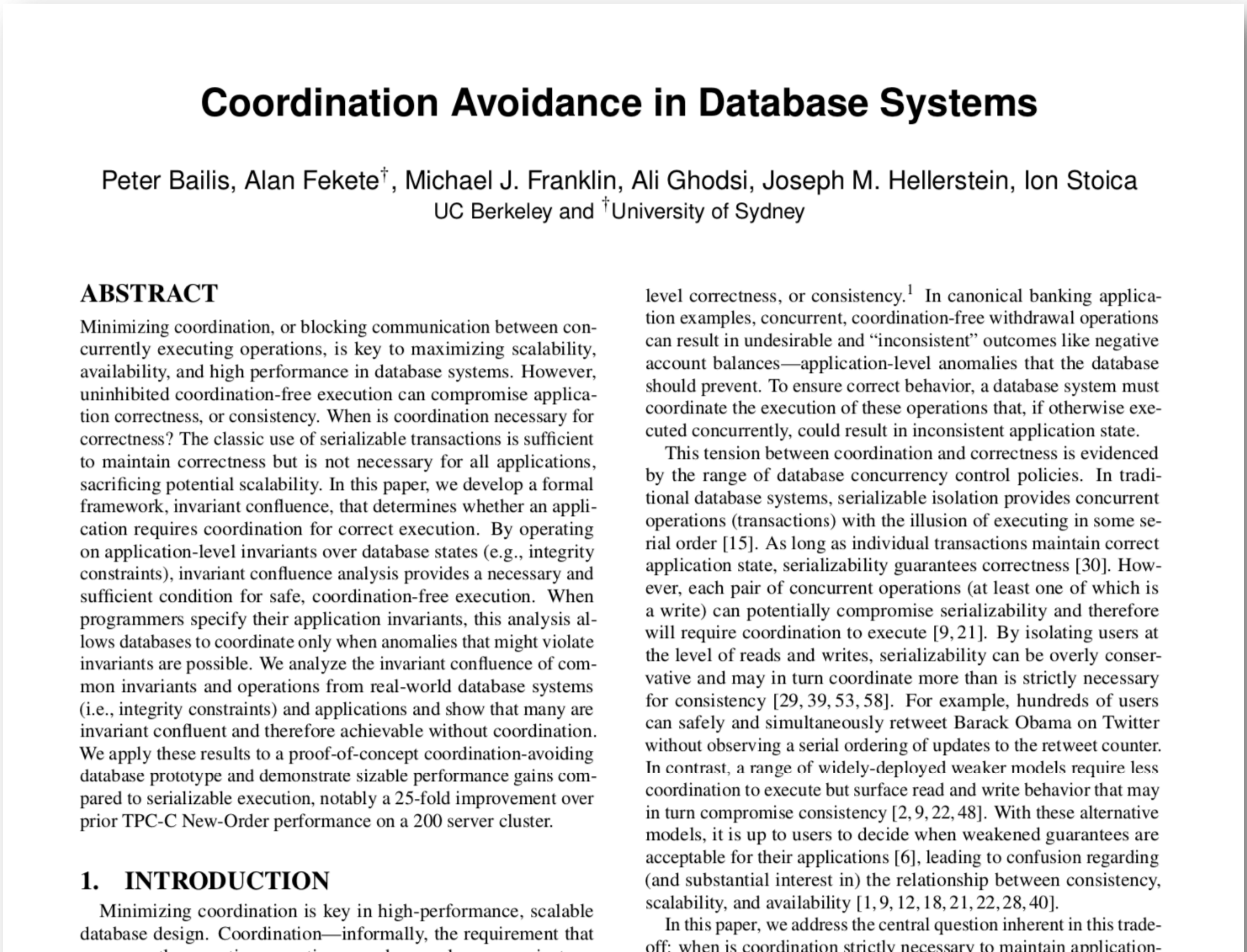
Do We Have to Coordinate?

Example: no user in DB has address=NULL

» If no replica assigns address=NULL on their own, then NULL will never appear in the DB!

Whole topic of research!

» Key finding: most applications have a few points where they need coordination, but many operations do not



Coordination Avoidance in Database Systems

Peter Bailis, Alan Fekete[†], Michael J. Franklin, Ali Ghodsi, Joseph M. Hellerstein, Ion Stoica
UC Berkeley and [†]University of Sydney

ABSTRACT

Minimizing coordination, or blocking communication between concurrently executing operations, is key to maximizing scalability, availability, and high performance in database systems. However, uninhibited coordination-free execution can compromise application correctness, or consistency. When is coordination necessary for correctness? The classic use of serializable transactions is sufficient to maintain correctness but is not necessary for all applications, sacrificing potential scalability. In this paper, we develop a formal framework, invariant confluence, that determines whether an application requires coordination for correct execution. By operating on application-level invariants over database states (e.g., integrity constraints), invariant confluence analysis provides a necessary and sufficient condition for safe, coordination-free execution. When programmers specify their application invariants, this analysis allows databases to coordinate only when anomalies that might violate invariants are possible. We analyze the invariant confluence of common invariants and operations from real-world database systems (i.e., integrity constraints) and applications and show that many are invariant confluent and therefore achievable without coordination. We apply these results to a proof-of-concept coordination-avoiding database prototype and demonstrate sizable performance gains compared to serializable execution, notably a 25-fold improvement over prior TPC-C New-Order performance on a 200 server cluster.

1. INTRODUCTION

Minimizing coordination is key in high-performance, scalable database design. Coordination—informally, the requirement that

level correctness, or consistency.[1] In canonical banking application examples, concurrent, coordination-free withdrawal operations can result in undesirable and "inconsistent" outcomes like negative account balances—application-level anomalies that the database should prevent. To ensure correct behavior, a database system must coordinate the execution of these operations that, if otherwise executed concurrently, could result in inconsistent application state.

This tension between coordination and correctness is evidenced by the range of database concurrency control policies. In traditional database systems, serializable isolation provides concurrent operations (transactions) with the illusion of executing in some serial order [15]. As long as individual transactions maintain correct application state, serializability guarantees correctness [30]. However, each pair of concurrent operations (at least one of which is a write) can potentially compromise serializability and therefore will require coordination to execute [9, 21]. By isolating users at the level of reads and writes, serializability can be overly conservative and may in turn coordinate more than is strictly necessary for consistency [29, 39, 53, 58]. For example, hundreds of users can safely and simultaneously retweet Barack Obama on Twitter without observing a serial ordering of updates to the retweet counter. In contrast, a range of widely-deployed weaker models require less coordination to execute but surface read and write behavior that may in turn compromise consistency [2, 9, 22, 48]. With these alternative models, it is up to users to decide when weakened guarantees are acceptable for their applications [6], leading to confusion regarding (and substantial interest in) the relationship between consistency, scalability, and availability [1, 9, 12, 18, 21, 22, 28, 40].

In this paper, we address the central question inherent in this trade-off: when is coordination strictly necessary to maintain application-

So Why Bother with Serializability?

For arbitrary integrity constraints, non-serializable execution can break constraints

Serializability: just look at reads, writes

To get “coordination-free execution”:

» Must look at application semantics

» Can be hard to get right!

» Strategy: start coordinated, then relax

Punchlines:

Serializability has a provable cost to latency, availability, scalability (if there are conflicts)

We can avoid this penalty if we are willing to look at our application *and* our application does not require coordination

- » Major topic of ongoing research

Outline

Replication strategies

Partitioning strategies

Atomic commitment & 2PC

CAP

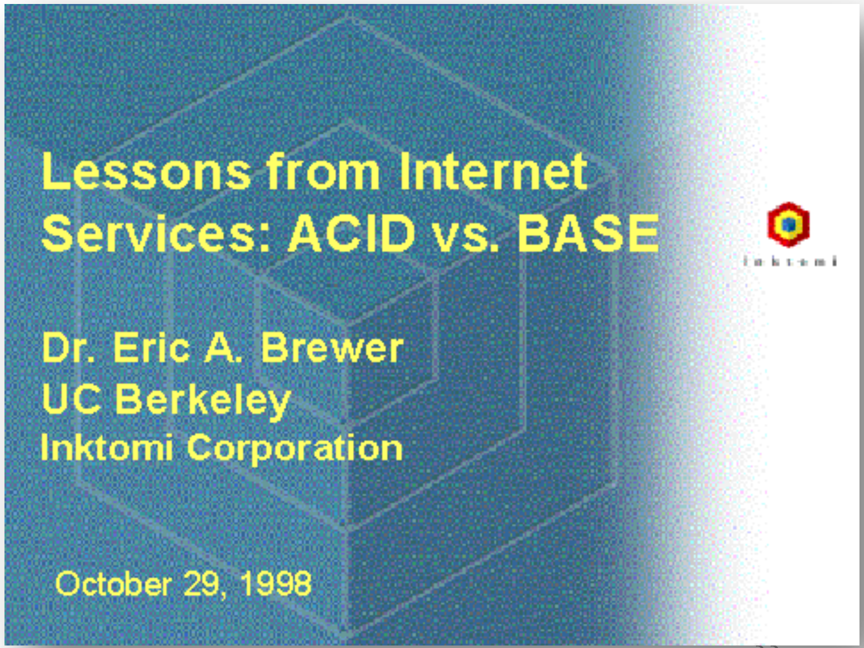
Avoiding coordination

Parallel query execution

Avoiding Coordination

Several techniques, e.g. the "BASE" ideas

» BASE = "Basically Available, Soft State, Eventual Consistency"



Lessons from Internet Services: ACID vs. BASE

Dr. Eric A. Brewer
UC Berkeley
Inktomi Corporation

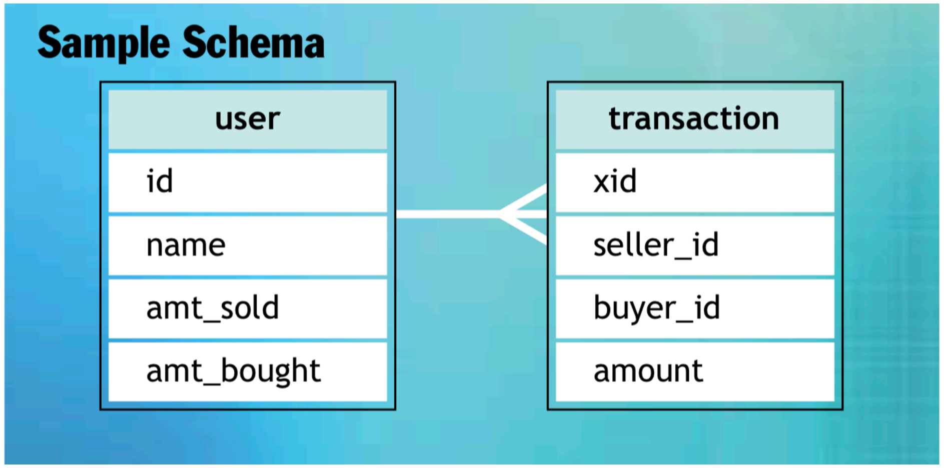
October 29, 1998

Avoiding Coordination

Key techniques for BASE:

- » Partition data so that most transactions are local to one partition
- » Tolerate out-of-date data (eventual consistency):
  - Caches
  - Weaker isolation levels
  - Helpful ideas: idempotence, commutativity

BASE Example

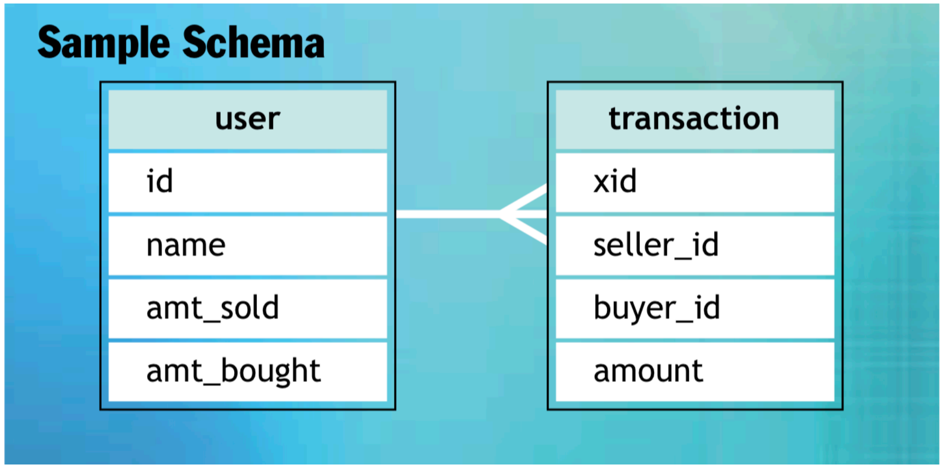


Constraint: each user’s amt_sold and amt_bought is sum of their transactions

ACID Approach: to add a transaction, use 2PC to update transactions table + records for buyer, seller

One BASE approach: to add a transaction, write to transactions table + a persistent queue of updates to be applied later

BASE Example



Constraint: each user's amt_sold and amt_bought is sum of their transactions

ACID Approach: to add a transaction, use 2PC to update transactions table + records for buyer, seller

Another BASE approach: write new transactions to the transactions table and use a periodic batch job to fill in the users table

Helpful Ideas

When we delay applying updates to an item, must ensure we only apply each update once

- » Issue if we crash while applying!
- » **Idempotent operations:** same result if you apply them twice

When different nodes want to update multiple items, want result independent of msg order

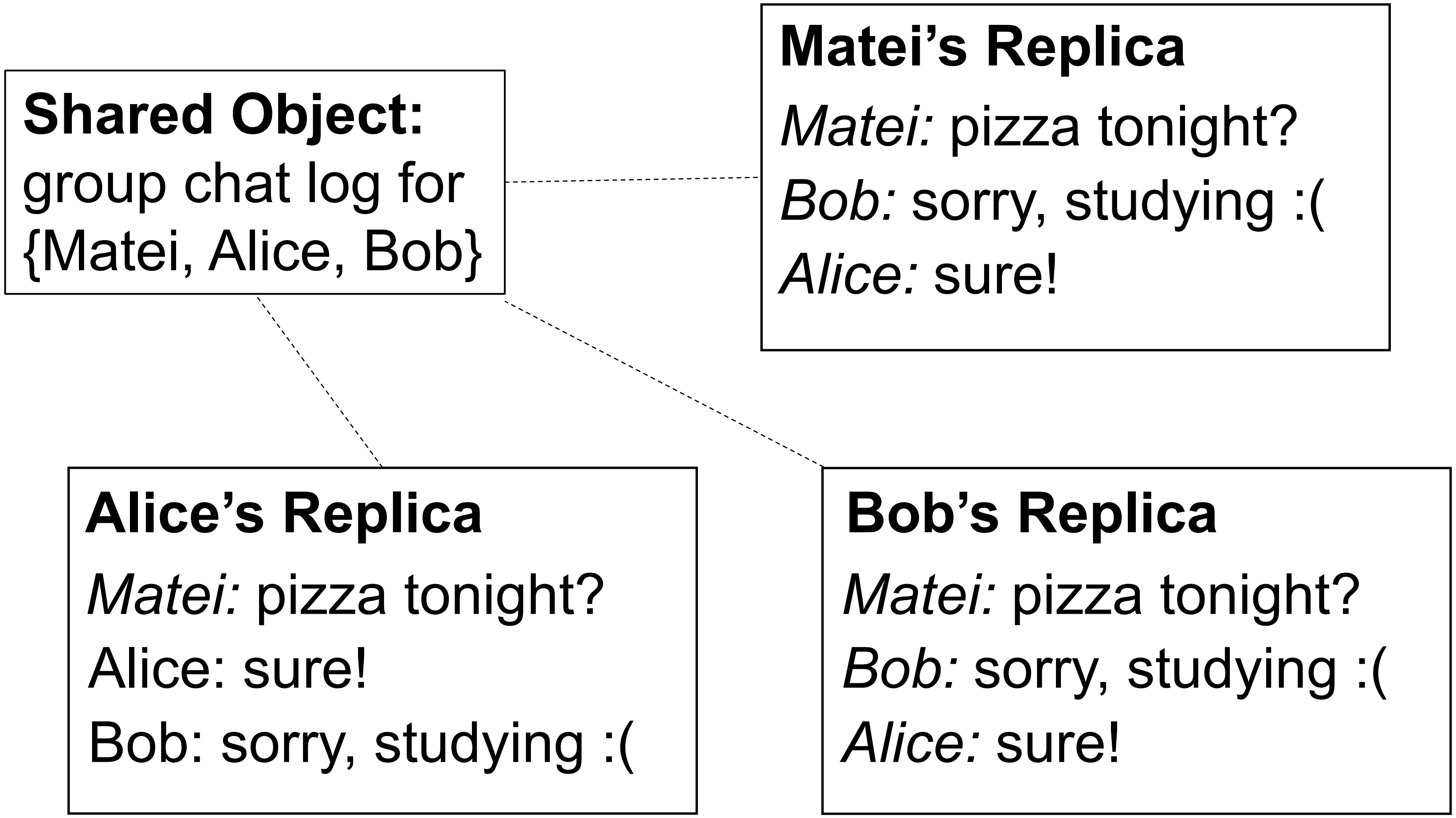
- » **Commutative operations:** $A \circledast B = B \circledast A$

Example Weak Consistency Model: Causal Consistency

Very informally: transactions see **causally ordered** operations in their causal order

» Causal order of ops: $O_1 \prec O_2$ if done in that order by one transaction, or if write-read dependency across two transactions

Causal Consistency Example



Shared Object:
group chat log for
{Matei, Alice, Bob}

Matei's Replica
Matei: pizza tonight?
Bob: sorry, studying :(
Alice: sure!

Alice's Replica
Matei: pizza tonight?
Alice: sure!
Bob: sorry, studying :(

Bob's Replica
Matei: pizza tonight?
Bob: sorry, studying :(
Alice: sure!

BASE Applications

What example apps (operations, constraints) are suitable for BASE?

What example apps are unsuitable for BASE?

Outline

Replication strategies

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CAP

Avoiding coordination

Parallel query execution

Why Parallel Execution?

So far, distribution has been a chore, but there is 1 big potential benefit: **performance**!

Read-only workloads (analytics) don’t require much coordination, so great to parallelize

Challenges with Parallelism

Algorithms: how can we divide a particular computation into pieces (efficiently)?

» Must track both CPU & communication costs

Imbalance: parallelizing doesn't help if 1 node is assigned 90% of the work

Failures and stragglers: crashed or slow nodes can make things break

Whole course on this: CS 149

Amdahl's Law

If p is the fraction of the program that can be made parallel, running time with N nodes is

$$T(n) = 1 - p + p/N$$

Result: max possible speedup is $1 / (1 - p)$

Example: 80% parallelizable $\Rightarrow$ 5x speedup

Example System Designs

Traditional “massively parallel” DBMS

» Tables partitioned evenly across nodes

» Each physical operator also partitioned

» Pipelining across these operators

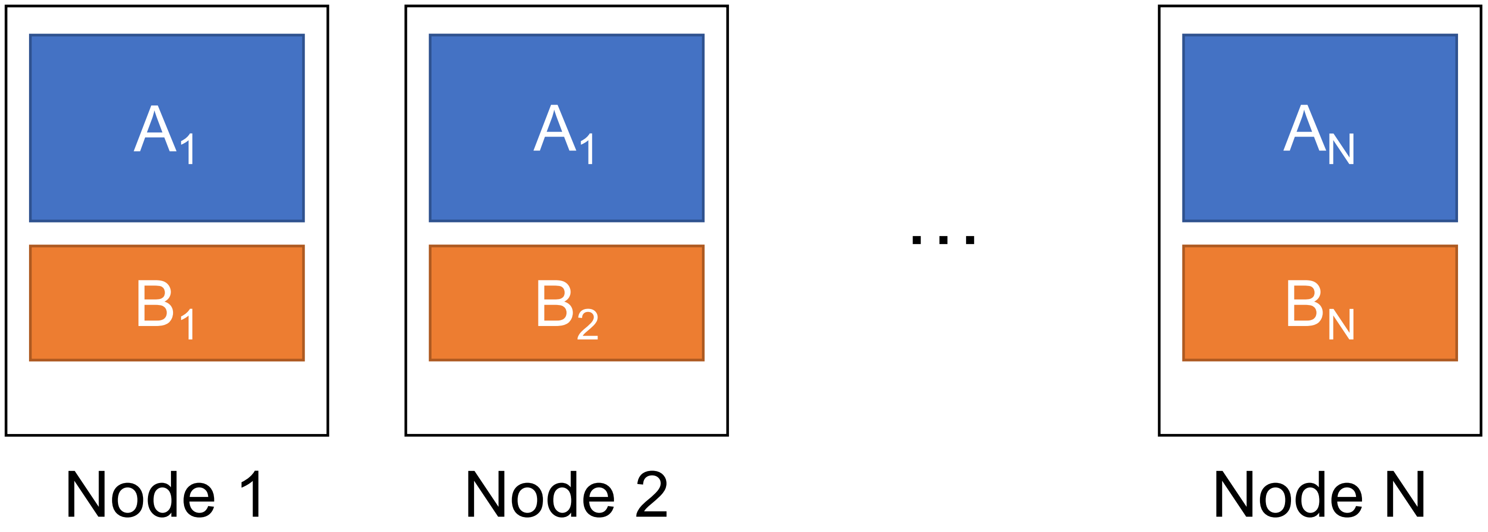
MapReduce

» Focus on unreliable, commodity nodes

» Divide work into idempotent *tasks*, and use dynamic algorithms for load balancing, fault recovery and straggler recovery

Example: Distributed Joins

Say we want to compute A ⋈ B, where A and B are both partitioned across N nodes:



Example: Distributed Joins

Say we want to compute A ⋈ B, where A and B are both partitioned across N nodes

Algorithm 1: shuffle hash join

- » Each node hashes records of A, B to N partitions by key, sends partition i to node I
- » Each node then joins the records it received

Communication cost: (N-1)/N (|A| + |B|)

Example: Distributed Joins

Say we want to compute A $\bowtie$ B, where A and B are both partitioned across N nodes

Algorithm 2: broadcast join on B

» Each node broadcasts its partition of B to all other nodes

» Each node then joins B against its A partition

Communication cost: (N-1) |B|

Takeaway

Broadcast join is much faster if $|B| \ll |A|$

How to decide when to do which?

Takeaway

Broadcast join is much faster if $|B| \ll |A|$

How to decide when to do which?

» Data statistics! (especially tricky if B derived)

Which algorithm is more resistant to load imbalance from data skew?

Takeaway

Broadcast join is much faster if $|B| \ll |A|$

How to decide when to do which?

- » Data statistics! (especially tricky if B derived)

Which algorithm is more resistant to load imbalance from data skew?

- » Broadcast: hash partitions may be uneven!

What if A, B were already hash-partitioned?

Planning Parallel Queries

Similar to optimization for 1 machine, but most optimizers also track data partitioning

- » Many physical operators, such as shuffle join, naturally produce a partitioned dataset
- » Some tables already partitioned or replicated

Example: Spark and Spark SQL know when an intermediate result is hash partitioned

- » And APIs let users set partitioning mode

Handling Imbalance

Choose algorithms, hardware, etc that is unlikely to cause load imbalance

OR

Load balance dynamically at runtime

- » Most common: “over-partitioning” (have #tasks ≫ #nodes and assign as they finish)
- » Could also try to split a running task

Handling Faults & Stragglers

If uncommon, just ignore / call the operator / restart query

Problem: probability of something bad grows fast with number of nodes

» E.g. if one node has 0.1% probability of straggling, then with 1000 nodes,

$$P(\text{none straggles}) = (1 - 0.001)^{1000} \approx 0.37$$

Fault Recovery Mechanisms

Simple recovery: if a node fails, redo its work since start of query (or since a checkpoint)

» Used in massively parallel DBMSes, HPC

Analysis: suppose failure rate is f failures / sec / node; then a job that runs for T·N seconds on N nodes and checkpoints every C sec has

$$E(\text{runtime}) = (T/C)\ E(\text{time to run 1 checkpoint})$$
$$= (T/C)\ (C\cdot(1 - f^N)^C + c_{\text{checkpoint}})$$

Grows fast with N, even if we vary C!

Fault Recovery Mechanisms

Parallel recovery: over-partition tasks; when a node fails, redistribute its tasks to the others

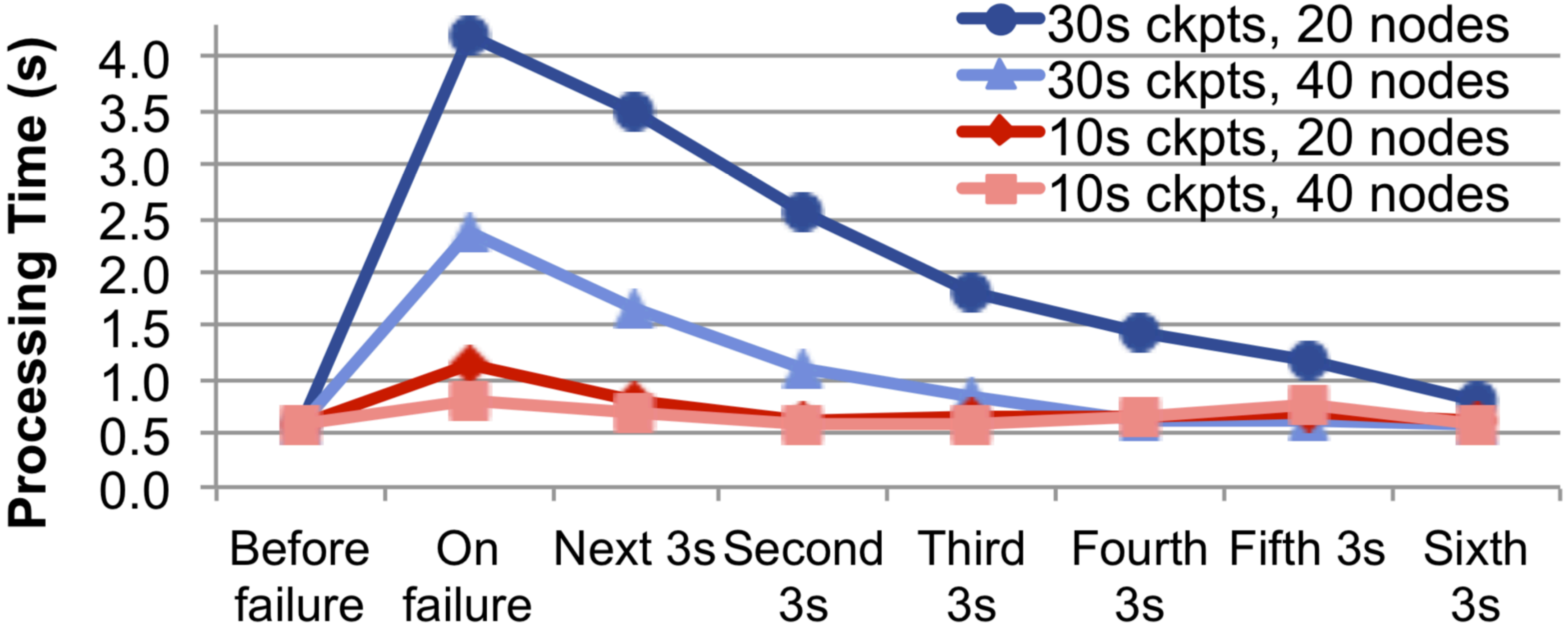
» Used in MapReduce, Spark, etc

Analysis: suppose failure rate is f failures / sec / node; then a job that runs for $T \cdot N$ sec on N nodes with task of size $\ll 1/f$ has

$E(\text{runtime}) = T / (1-f)$

This doesn't grow with N!

Example: Parallel Recovery in Spark Streaming



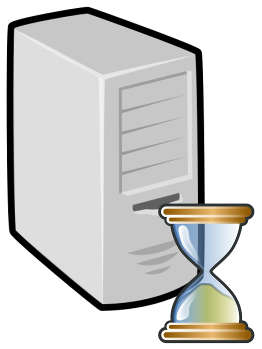
From "Discretized Streams: An Efficient and Fault-Tolerant Model for Stream Processing on Large Clusters"

Straggler Recovery Methods

General idea: send the slow request/task to another node (launch a "backup task")

Threshold approach: if a task is slower than 99th percentile, or 1.5x avg, etc, launch backup

Progress-based approach:
estimate task finish times and launch tasks likeliest to finish last



$$est\ finish\ time = \frac{work\ left}{progress\ rate}$$

Summary

Parallel execution can use many techniques we saw before, but must consider 3 issues:

- » **Communication cost:** often $\gg$ compute (remember our lecture on storage)
- » **Load balance:** need to minimize the time when last op finishes, not sum of task times
- » **Fault recovery** if at large enough scale