

# Distributed Systems

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## 1 System Models

- In a **synchronous** message passing system, there exists some known finite bound  $\Delta$  on message delays. That is, for any message sent, an adversary can delay its delivery by at most  $\Delta$ . So, every process that sends messages at time  $t$  gets them delivered by time  $t + \Delta$ . i.e., the whole system runs in lockstep, marching forward in perfectly synchronous rounds. For example, [ADD<sup>+</sup>19] provides a standard (modern) description of the synchronous model:

If an honest party  $i$  sends a message to another honest party  $j$  at the beginning of a round, the message is guaranteed to reach by the end of that round. We describe the protocol assuming lock-step execution, i.e., parties enter and exit each round simultaneously. Later...we will present a clock synchronization protocol to bootstrap lock-step execution from bounded message delay.

- In a fully **asynchronous** model, there is no upper bound on the delay for a message to be delivered, but we do assume that the delay is some finite value (e.g. chosen by an adversary). So, even though the message delay may be some unknown/unbounded quantity, we do assume that every message eventually gets delivered, even if the delay is unknown a priori.

The nature of asynchronous networks also implies that there is no way to have a perfect failure detector in a fully asynchronous system, since you can't distinguish between a failed/stopped process and one whose messages are just taking a long time to get delivered.

- The **partial synchrony** model aims to find a middle ground between the two above models. The assumption is that there exists some known finite time bound  $\Delta$  and a special event called GST (global stabilization time) such that:
  - The adversary must cause the GST event to eventually happen after some unknown finite time.
  - Any message sent at time  $x$  must be delivered by  $\Delta + \max(x, GST)$ . That is, after the GST, messages are delivered within the known finite time bound  $\Delta$  (i.e. the system has “reverted” to synchrony).

*What are the fundamental differences between the synchronous and asynchronous models, and what exactly makes the latter harder?*

## 2 Causality and Clocks

In general, we can view a distributed system as consisting of a set of *events* that occur over time at different physically located nodes in the system. If these nodes do not communicate, there is no natural way of ordering these events with respect to each other, aside from those events which occur locally on some node, which can be ordered with respect to each other in the natural way.

When nodes can communicate, one natural way to order events is not using real-time, but using causal relationships between events. That is, we consider which set of events could *causally affect* a certain event. When sending a message between nodes  $A$  and  $B$ , this establishes a causal dependency between events on those nodes i.e. events after the receipt of a message on  $B$  could have been influenced by events on  $A$  occurring at or before the sending of the message.

One way to formalize this notion is through the framework of *causal histories* [BP16]. That is, every local node executes events in order, tagging each event with its node id and a monotonically increasing logical timestamp. Each event in the system then keeps track of

FIGURE 2: CAUSAL HISTORIES

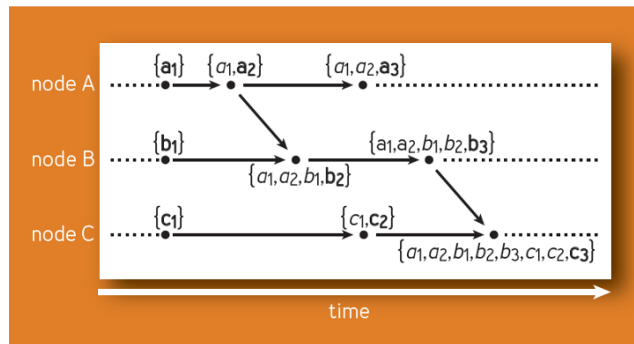


Figure 1: Causal history example.

its current identity, but also its *causal history* i.e. the events that could have influenced it. For local node events, we can do this by simply *merging* the current event with the causal history of the previous event (e.g. a local event's causal history always includes all previous events on that node). For distributed events, upon message receipt event  $m_r$  for message send  $m_s$ , we merge the causal history of  $m_s$  with the causal history of  $m_r$  to form the new causal history of  $m_r$ . We can see this in Figure 2 e.g. When node  $B$  executes event  $b_2$ , which is the receipt of a message from  $A$ , its new causal history contains its existing causal history of  $\{b_1\}$ , merged with the causal history of event  $a_2$ , which is  $\{a_1, a_2\}$ .

In this model, to compare two events  $e_1$  and  $e_2$ , we can simply compare their causal histories directly. Specifically, we can say that  $e_1$  causally precedes  $e_2$  if and only if the causal history of  $H_{e_1}$  is a strict subset of the causal history of  $H_{e_2}$ , i.e.  $H_{e_1} \subsetneq H_{e_2}$ . This makes sense, since, if  $e_1$  could have causally influence  $e_2$ , there must be some causal path leading from  $e_1$  to  $e_2$ , and, by the merging property of causal histories, this would imply that the causal history of  $e_1$  ended up being merged into the causal history of  $e_2$ . Note that this also allows us to definitively say whether  $e_1$  and  $e_2$  are *concurrent* i.e. neither causal history is a subset of the other iff they are concurrent i.e. there is no definitive causal relationship between them.

## 2.1 Vector Clocks

The above view of causality via causal histories is logically straightforward, but it could be costly in a system to maintain full sets of causal event histories and pass them around between nodes. A more efficient approach is to use *vector clocks* [Fid88], which can be viewed as essentially a compact representation of causal histories. Basically, since we know that any event on a local node will always contain all previous events on that node in its causal history, we don't need to store the full set of events in each causal history.

Rather, we can simply store, for each node, the *newest* event that occurred on that node, giving us a *vector* of timestamps for each node that are stored and propagated between nodes. Then, we can translate the original rules for causal history merging into this compact

FIGURE 3: VECTOR CLOCKS

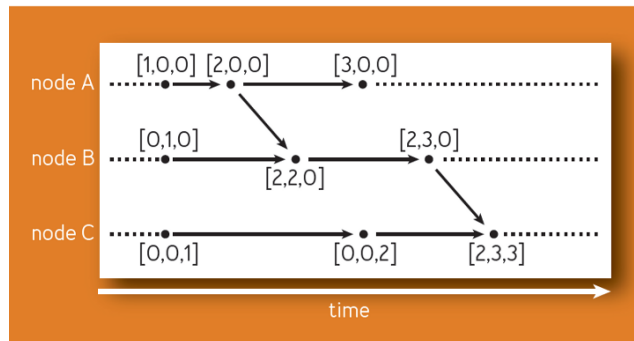


Figure 2: Vector clocks example.

representation. Basically, when a new local event occurs, we simply need to advance the timestamp counter for that node's entry in the vector. And, when a message is sent between nodes, the "merging" operation of the causal histories above simply becomes a *maximum* operation. That is, we take the element-wise maximum between the receiving node's vector and the sending node's vector, which gives us the new vector for the receiving node, after

also incrementing the receiving node’s timestamp counter to account for the message receipt event. This is shown in Figure 2.

With this vector clock representation, we can also translate the *subset* comparison check from the causal history formulation. We know that one time  $v_1$  will causally precede  $v_2$  iff all elements of in the vector  $v_1$  are  $\leq$  those of  $v_2$ , *and* they are not equal (alternatively checked by seeing if at least one element of  $v_1$  is strictly smaller). This allows us to view vector clocks as simply a compact representation of the natural, causal history formulation.

## 2.2 Lamport Clocks

Although Lamport clocks are sometimes presented as an earlier incarnation of logical timestamps, in some sense vector clocks are actually the more natural incarnation of this idea, since they can be viewed as described above as being directly derived the the underlying causal history framework. We can, however, consider other, more compact ways to order events across nodes. In general, we want an ordering system that respects the true causal ordering (as defined above with causal histories), but that doesn’t ever give us a firmly wrong answer about causal ordering of events. In essence, the true causal structure of a system is represented as the full acyclic graph, with all causal dependency edges between events.

If we tag events only with a single logical timestamp, and ensure that events increment/update their timestamps in accordance with causal event order, we throw away node identity, but can still preserve some of the causal information between nodes. If two events are causally related  $a \rightarrow b$ , then we know that the timestamp of  $a$  will be strictly less than the timestamp of  $b$ . But, the converse is not true, since we can have events that are concurrent, which will have the same timestamp.

TODO: Some more notes here.

## 3 Fault Tolerance

There are some fundamental requirements to establish bounds for fault tolerance in an omission fault model. If an arbitrary set of  $f$  nodes can fail by stopping at any time, then this means that if we want a protocol that makes progress, we would need to ensure that any “work” we do (e.g. executing operations, writing down data, etc.) is made sufficiently redundant so that it can be accessed even in the case of maximum node failure. So, this implies we need to write all data to at least  $f + 1$  nodes, so that there is always at least one non-faulty node with the data we need to access.

This seems to imply that having  $f + 1$  nodes might be sufficient for a protocol to be fault tolerant. But, this doesn’t satisfy a progress requirement. That is, if we now need to write everything down to  $f + 1$  nodes, then failure of  $f$  out of  $f + 1$  nodes would clearly stall our protocol, since it can’t do any work safely. So, our additional requirement is that both:

- 1) Write any work down to  $f + 1$  nodes.
- 2) Always have  $f + 1$  non-faulty nodes available that we can write work down on.

Thus, this naturally gives us a total node requirement of

$$n = (f + 1) + f = 2f + 1$$

That is, even in the case of  $f$  maximum node failures, we will always have  $f + 1$  nodes available to us to write down our work, allowing us to make progress.

## 4 Distributed Transactions

In order to achieve ACID guarantess of classic database systems in distributed setting, we typically rely on some kind of distributed transaction commit protocol (e.g. two-phase commit). The classic, gold standard approach for doing this in a distributed setting is to use some variant of two-phase commit protocol [BHG86]. That is, we essentially ask multiple, separate partitions of the database data to *prepare* to commit their transactions (e.g. taking locks or marking the appropriate records) before we go ahead and *commit*, if all partitions agree.

### 4.1 Optimizing Two-Phase Commit

In modern distributed database systems, a common architecture was to horizontally scale data by partitioning (e.g. sharding) and vertically scale for fault tolerance by having each shard run some kind of replication or consensus protocol (e.g. Paxos). This is more or less

the approach taken by systems like Google’s Spanner [CDE<sup>+</sup>12], which chunks up data into shards and runs a Paxos group/instance per-shard. Then, for running transactions across shards, it uses a variant of two-phase commit to run transactions at each shard that contains data involved in a transaction. This was also predated by related systems like Percolator [PD10] and Megastore [BBC<sup>+</sup>11].

These approaches can incur high latency, though, since 2PC + Paxos replication incurs a lot of round trips to commit a transaction. Optimizations of these various distributed two-phase transaction commit protocols appeared in similar time period, including MDCC [KPF<sup>+</sup>13] and TAPIR [ZSS<sup>+</sup>15]. Unanimous 2PC [JHKM24] is a more recent approach that also gives a good overview of optimized commit protocols in this theme.

## 4.2 Deterministic Transaction Scheduling

Approaches like Calvin [TDW<sup>+</sup>12] take advantage of deterministic transaction scheduling to avoid the cost of full 2PC. Statically scheduling the transactions upfront at a *sequencer* process allows execution of transactions with guarantee of no conflicts, avoiding need for 2PC costs. This can often assume a one-shot transaction model, though, since a transaction’s full read/write sets are typically required in order to check conflicts when scheduling.

## 4.3 Isolation

Classic database isolation levels have been re-examined and/or re-implemented in context of distributed transaction systems. *Parallel snapshot isolation* (PSI) [SPAL11] is one example of this. In the classical definition of *snapshot isolation*, transactions must read from a snapshot that reflects a single global commit order of transactions, and transactions that write to the same key cannot run concurrently. PSI relaxes this by allowing transactions, for example, to commit in different orders at different geo-replicated sites, as long as they don’t have any causal relationship to each other.

### 4.3.1 State-Based Model

Crooks’ [CPAC17] isolation model takes a *client-centric* view, centering the isolation formalism around the client visible states that can be observed by a client. Essentially, it views any set of transactions as moving through a sequence of states (via an execution of those transactions) which produces some sequence of states, parts of which may or may not be observed by transactions in this execution.

More formally, we say that for a set of transactions  $\mathcal{T}$ , an execution  $e$  is a total order of those transactions, along with a set  $S_e$  of states that can be produced by this execution of those transactions.

$$s_0 \xrightarrow{T_1} s_1 \xrightarrow{T_2} s_2 \xrightarrow{T_3} s_3 \xrightarrow{T_4} s_4$$

For defining a given isolation level we then define a *commit test*,  $CT$  which basically defines validity conditions for each transaction in such an execution and its possible ”read states” i.e. the set of states in the  $S_e$  its operations could have read from.

$$\exists e : \forall T \in \mathcal{T} : CT(T, e)$$

Note that the execution  $e$  defines a total order on transactions (i.e. as if they were executed in some total order). But, this doesn’t necessarily imply that a ”true” or unique total order exists.

For example, under serializability, the commit test says that there exists an execution  $e$  such that for every transaction  $T$  and its parent state  $s_p$ , the following holds:

$$\text{COMPLETE}_{e,T}(s_p)$$

That is, the parent state of  $T$  is a complete state, meaning all reads in  $T$  could have read from state  $s_p$ . Clearly, though, if two transactions are not causally related (e.g. they read and write disjoint sets of keys), we could order them arbitrarily in any execution, so the total order of such a chosen execution may in fact be more concrete/prescriptive than necessary e.g. there may really only be a partial ordering between some transactions.

### 4.3.2 Various Isolation Formalisms

Another modern formalization of transaction isolation levels is that of [CBG15], which is based on *arbitration* and *visibility* relations between committed transactions. Essentially, in their model, they only consider isolation levels as weak as *read atomic* i.e. models where either *all* or *none* of the writes of a transaction are visible to another transaction. This

means they cannot express things like *read committed* in their model, since this requires expressing cases where different reads in a transaction essentially see views of the database state that differ with respect to who wrote the values of those keys (e.g. akin to two reads reading from different snapshots). In this sense Crooks’s state-based model is more general, since it allows for definition of isolation levels where different read operations within a transaction observe different prior read states.

Note that it is worth considering how these different models of transaction isolation define their conditions. In all models, it seems we ultimately care about defining correctness conditions over *a set of committed transactions*,  $\mathcal{S}$  since we don’t really care about correctness conditions on transactions that abort or are in-progress. Furthermore, how do we think about the relationship between reads and writes? Really, reads are the only way we can ever observe the state of the database, and so really our correctness conditions should ultimately say something about how reads are correct w.r.t previous writes. For example, if we have a set of transactions that only do writes, or a set of transactions that only do reads, there are really no nontrivial conditions for correctness (e.g. for read only transactions we would assume all transactions always read the same, empty state). So, correctness conditions on isolation really need to be conditions on reads to the extent that they observe something that could be consistent with some execution of the writes in the set of committed transactions.

As a basic condition, we should presumably always want the read of a key  $k$  to always return a value that reflects the value written by *some* transaction in the committed set  $\mathcal{S}$ . Moreover, we probably want our database to behave *as if* it executed the set of committed transactions in some consistent order. This doesn’t necessarily imply serializability, since we are only saying that we expect what we read to be consistent with *some* state the database could have passed through in the past (assuming it behaves as if there is some sequential order of transaction execution).

Part of transaction isolation conditions are about determining

1. What are the valid set of states of a transaction could possible read from?
2. From these possible states, which are the ones I could be valid to read from under some isolation conditions?

If your answer to (1) involves defining valid states in terms of some sequential execution of committed transactions, then this seems to naturally imply you need some way of (1) ordering transactions and (2) ensuring that the values observed by transaction reads reflect this sequential ordering accurately.

Note about parallel snapshot isolation (PSI) which seems really about relaxing isolation in *replicated* systems i.e. could a secondary apply transactions in a different order than a primary. Question is whether database truly commits to a sequential execution of all transactions. This seems like a notable example of where it may not e.g. if two transactions are concurrent, their ordering across primaries/secondaries is allowed to be different?

## 5 Consensus

The problem of *consensus* in a distributed system is to get a set of separate nodes to agree on a single value. That is, if one node marks a value as chosen, no other node can ever mark a different value as chosen. To understand the constraints of how we might solve this problem, we can start by thinking about this problem in a simpler setting e.g. a single (non-distributed) node. For an individual node/thread, solving consensus is trivial, since that node/thread can just write into a single register and then never change its decision. But, even when we introduce multiple concurrent clients (e.g. threads), the problem is nontrivial.

### 5.1 Shared Memory Consensus: Lock-based

We assume we have a single register which represents our consensus “object”, and we have multiple threads that can access the register. That is, they can read or write a value to the register atomically. If we have a locking primitive available, then we can solve the single register consensus problem easily. Each thread just acquires a global lock before it tries to do anything, reads the register to check if it has already been written to, and if it has, then do nothing, and if it hasn’t, then go ahead and write whatever value you want. It is obvious to see that this upholds the basic correctness properties of consensus.

### 5.2 Shared Memory Consensus: Lock-less

Now, what if we want to consider solving the above problem without locks? And why would we need to do this? Well, first, we can imagine that if we eventually want a solution that generalizes to the distributed setting, we won’t be able to rely on locks as a fundamental

mutual exclusion primitive, since a global lock primitive won't exist in a distributed setting. Additionally, locks necessarily present a potential impediment to system progress, if we assume that threads can fail or run slowly. That is, if locks can be taken unilaterally by some thread and only released by that thread, this presents potential liveness issues if that thread fails to make progress for some time and other nodes cannot proceed. So, coming up with a lock-less solution to the consensus problem seems a reasonable/desirable goal (isn't there a trivial solution to this, though, in shared memory setting?).

### 5.2.1 Trivial Solution: Compare and Swap (CAS)

First, a trivial consensus algorithm for a single register in the shared memory context is just to use compare&swap (CAS) when attempting to update the register. Each process just runs  $CAS(X, \perp, v)$  to update the register  $X$  to value  $v$  only if it hasn't been set, where  $\perp$  represents the empty/unset register value. The first writer always wins and consensus is achieved. See this described briefly in Theorem 5 of [Her91], which establishes that CAS register has an infinite consensus number. But isn't this kind of cheating? Like, don't we want to figure out a way to do consensus with weaker forms of atomic primitives? Also, if we move to a truly distributed/fault-tolerant setting, we can't necessarily assume we have a global register which we can just CAS easily like this?

**Remark on CAS** Note that *compare&swap* primitive is kind of just implementing "lock like" mutual exclusion at a lower level i.e. for register  $X$

```
CAS(X, old, new):
    if X == old:
        X := new
        return true
    return false
```

That is, it basically allows you to do a read and a write atomically, as if you were doing it under a "virtual" lock. It's just that in practice, this "lock" isn't explicit and failure while holding a lock isn't an issue, since the operation is truly atomic, and if such a failure occurs, the whole operation would be aborted and this kind of "virtual" lock automatically released.

### 5.2.2 Generalizable Solution

Although the CAS solution works trivially in a single node setting, ultimately we want to build up to a solution that actually works in a distributed setting. We could argue, though, that in a single machine setting, if you have a CAS primitive, then consensus is always trivially solved, as long as you assume that the CAS register itself doesn't "fail". Part of the tricky part is that if we want to have true fault tolerance, we will probably want to assume that a whole machine (including such a CAS register) may fail, so we want to distribute across multiple machines, which means that, for fault tolerance, we necessarily can't rely on writing to just one machine. So, we are going to necessarily give up the atomicity provided to us by a CAS primitive. Thus, we basically need to re-implement a CAS primitive across a truly distributed set of storage nodes. To do this, we can think more precisely about the requirements of consensus even for the lock-based or CAS solutions, and see how to satisfy them even for the distributed case.

If we think about the fundamental requirements of consensus in this "single register" model, it boils down to a simple high level requirement that threads must satisfy:

R1. If a thread writes a value  $v$  to the register, then it should not differ from the most recently written value.

This is the very basic, fundamental requirement, simply stating that whenever somebody tries to write to the register they better not overwrite an already existing, different value in the register. In order to start working out a lock-less solution to the problem, let's consider how the lock-based solution satisfies this above requirement.

In the lock-based solution we can think about every thread as executing a simple request/transaction, that consists of the following steps:

```
acquire(lock)
if read(X) is not set:
    write(X, v)
release(lock)
```

where `lock` is the global lock shared by all threads, and `X` represents our register object, and `v` is some arbitrary value the thread chooses to write. How does such a procedure satisfy the above requirement R1? Well, first, the locking mechanism ensures that all operations are explicitly/globally ordered with respect to each other i.e. their order is dynamically assigned based on the order of lock acquisition. Based on this, it is clear then, that

- C1. Reads by transaction  $T$  read the value written by the most recent transaction ordered earlier than  $T$ .
- C2. After a transaction  $T$  that is currently holding the lock completes its read, no future writes will ever be made by transactions ordered earlier  $T$ .

Note that (C2) is an important but subtle condition that is required for safety. Simply reading the most recently written value is not sufficient to ensure correctness, since this doesn't say anything about writes that may occur *after* the read but *before* the subsequent write of the transaction. In other words, you need to protect against concurrent transaction writes that would invalidate the results of your read.

Ok, so let's try to take these ideas and turn them into a generalizable solution. Note that the core requirements above are essentially the same for a lock based or CAS based single node solution. The key properties above are always essentially enforced the underlying atomicity of either a lock-based or CAS based solution. One main idea is that there is an implicit order/sequence assigned to all transactions in the lock-based approach. We might say this ordering is "implicit" or "on demand" because transactions don't really get ordered until they try to go ahead and acquire a lock. At that point, we can imagine them being implicitly assigned some sequence number in a global sequence of transactions based on the order of their lock acquisition. So, if we don't want to rely on locks, but we know that this global ordering notion works for a lock-based solution, can we try to develop an ordering mechanism that doesn't rely on locks?

Well, the naive approach is to basically just pre-assign global, totally ordered sequence numbers to all transactions. There might be a variety of schemes for doing this, but if we're still in a single machine context, we could imagine simply having a global atomic counter that hands out sequence numbers to transactions before they start. Alternatively, we could hand out disjoint, evenly distributed sets of sequence numbers to each thread at system initialization, that they can draw from whenever they want to start a new transaction. For simplicity, we can kind of ignore the details of how such an ordering assignment scheme works, but we can assume that there is some way to assign uniquely global, totally ordered sequence numbers to different transactions (note that Paxos similarly does this in a similar manner, by pre-assigning disjoint sets of proposal ids to to each proposer).

If we now assume that all transactions are tagged with a unique, totally ordered sequence number, we can try to use this to build a complete, lock-less solution to the single register consensus problem. As shown above, each thread can still execute a similar procedure as before, but it will do so without acquisition/release of locks and with a bit of extra checking related to their sequence numbers. As we said above, all that threads need to ensure are conditions (C1) and (C2). Let's consider them independently, starting with C2 first.

- (C2) This condition is fairly straightforward to handle. Whenever transaction  $T$  with sequence number  $n$  does a read, it can tag the register with sequence number  $n$ . Then, subsequent writes from transactions in sequence numbers  $k$  can check their sequence number against  $n$ . If  $k < n$  then we can prevent the write from occurring, and if  $k \geq n$ , then we can allow the write to succeed. This clearly ensures that once a read occurs by transaction in sequence number  $n$ , no future writes can be made to the register by transactions ordered  $< n$ .
- (C1) This condition is a bit more tricky, since it is complicated by the fact that we no longer assume a global serialization order between transaction operations as we did in the lock-based solution. For example, if we make a fundamental assumption that transaction operations may be always be interleaved in arbitrary orders (based on the fact that we have no global locking/mutex primitive), how can we possibly satisfy C1 in a case like the following,

```
read:2(X)
write:1(X, v)
```

where `op:seqno` indicates that `op` is an operation from transaction with sequence number `seqno`? That is, how can we ever enforce that a read from transaction at sequence number  $n$  will necessarily see the writes from transactions at sequence numbers  $< n$ , if it can't forcibly protect against such transactions doing writes after the transaction

in  $n$  does its read? Well, we can't really be sure, if we make the fundamental concurrency/interleaving assumption above. So, this is where our solution to dealing with C2 comes into play. Instead of trying to ensure C1 exactly, we just explicitly prevent any future writes that would violate it. If some writes have already occurred in sequence numbers  $< n$ , then we will obviously read their effects when we read at transaction  $n$ , but then after we read at  $n$ , we just force the system to never execute a write at a transaction number  $< n$  in the future. Note also that we aren't really impairing ourselves unnecessarily here. That is, once a transaction in sequence number  $n$  has started, we make the implicit assumption that it "overrules" any transactions in earlier sequence numbers, so there's not really any point in letting an earlier transaction go ahead and write when a higher transaction number has already started anyway. So, we can view it as acceptable to just prevent/discard these "stale" writes anyway.

Ok, so now that we worked out how to ensure the two important correctness conditions above, we get to a final, lock-less procedure for each thread that looks like the following, where we now assume that alongside the register there also sits a "version" number register  $V$  that can also be written and read by threads. (TODO: really this should be the distributed implementation, where storage registers now live on each node, and we write to them tagged with version numbers to implement the CAS op.) Note that really, at its core, we should be able to see Paxos/consensus as simply implementing the following bit of atomic code:

```

if read(X) is set:
    return
write(X, v)

```

With a CAS primitive on a single machine this is trivial, but if you want true fault tolerance you're going to necessarily have to distribute your storage of the written value across multiple machines, and therefore you lose out on the fundamental atomicity provided by the CAS primitive to do the read-write transaction above atomically. So, you re-implement this in a distributed setting by basically first deconstructing the basic properties that such a transaction satisfies that are sufficient for correctness, and then just re-implement these in a distributed fashion. And basically, these properties are pretty much just the standard properties you get from serialized transactions of the above form i.e. firstly that all transactions are implicitly assigned a global, totally ordered serialization order and (1) a read observes the value of the most recent write and (2) once a transaction is in progress, no transactions ordered earlier than it can do any more writes. This is basically all that is needed to ensure safety of a CAS based consensus procedure, and this is essentially the exact same conditions that you need to satisfy in a distributed variant of this (i.e. Paxos). To enforce ordering you use pre-assigned sequence numbers, and then you just tag all your operations with your sequence number and behave appropriately to ensure that you don't violate the above 2 conditions at any time. For example, if you see that a transaction in a higher sequence number has started doing operations, then you need to prevent yourself from doing any writes to ensure you don't violate (2). And, when you do a read, if you see written values in some various sequence numbers, then you need make sure you read the value in the highest sequence number. Note that it should be perfectly fine to abort if you see some previously written values in lower sequence numbers, too, but I think you want to be optimistic in cases where earlier writes were only "partially" completed, which is something that can happen in a distributed setting that doesn't exist in the world of single node CAS. So, this is one other thing that changes a bit fundamentally in the distributed vs single node CAS setting.

```

// Procedure for transaction with sequence number N.
if read(V) > N:
    return
write(V, N)
if read(X) is not set:
    write(X, v)

```

But what if we can't atomically read and write the version number register? (TODO...) Perhaps [Her91] is the reference I'm looking for here. Note one of their main claims:

From a set of atomic registers, we show that it is impossible to construct a wait-free implementation of (1) common data types such as sets, queues, stacks, priority queues, or lists, (2) most if not all the classical synchronization primitives, such as *test&set*, *compare&swap*, and *fetch&add*, and (3) such simple memory-to-memory operations as move or memory-to-memory swap.

Note the following table of consensus numbers of some objects:



Consensus Number	Object
1	read/write registers
2	test&set, swap, fetch&add
$\vdots$	$\vdots$
$2n - 2$	$n$ -register assignment
$\infty$	compare&swap

See also [AH90] as possibly relevant.

(In Paxos phase 1b, do acceptors actually have to do some atomic read-write transaction in order to check if given proposal number is newer than their own...?)

### 5.3 Paxos

Paxos is a protocol for implementing consensus in an asynchronous distributed system assuming crash faults. Modeled as *proposers*, *acceptors*, and *learners*, and consists of 2 main phases, *Prepare* and *Accept*. Proposers, which each own a disjoint set of a ballot space, propose values in one of their designated ballots, and send a *Prepare(b)* message for this ballot to a quorum of acceptors. Acceptors will respond to a *Prepare(b)* message if it is newer than the latest ballot they know about. A proposer, hearing a quorum of *Prepare* responses, then sends out an *Accept(b, v)* message for that ballot, where  $v$  is chosen either as the value with the highest ballot it hear about in *Prepare* phase, or as any value the proposer desires. Acceptors accept a value via an *Accept* message if the ballot is not older than their own latest known ballot. A value is committed at a ballot  $b$  if a quorum of acceptors have accepted that value at  $b$ .

### 5.4 Vertical Paxos

The classic consensus problem for Paxos is defined on a fixed set of  $n$  processes. In practice, though, as nodes fail over time we may need to remove them from the system and add in new ones, via *reconfiguration*. In standard “horizontal” Paxos algorithms, like the approach described in [Lam01], the set of servers is made a part of the state machine state, and special “reconfiguration” commands on the state machine modify this set of servers. If the set of servers can change, though, then there needs to be some way of determining which set of servers implement what instances of the consensus algorithm. In one of Lamport’s original suggested approaches, we can allow a configuration command at instance  $i$  to take effect at instance  $i + \alpha$ . So, we can propose commands up to  $\alpha$  slots after the reconfiguration, but no further, until we know whether the reconfiguration committed, so that we are sure we know the correct set of servers to consider.

In the above, “horizontal” Paxos approach, configurations change across Paxos instances, in accordance with the *horizontal* reconfiguration commands. *Vertical Paxos* [LMZ09] differs in that it allows for reconfiguration *across Paxos ballots*, even within the same instance. This is the “vertical” notion i.e. if you imagine instances as moving horizontally and Paxos ballots per instance laid out vertically. In the Vertical Paxos, they basically assume the existence of an external master that stores the configuration state across ballots, which itself can be implemented using state machine replication. Essentially, when a reconfiguration occurs in Vertical Paxos, the new configuration becomes active right away, and the previous configuration remains active only for storing old information, and the new one accepts new commands. When the state of the previous configuration has been transferred to the new configuration, the new leader of the new config tells the master this is done, and the master can inform all future leaders that it no longer needs to contact the old configuration i.e., it deactivates the old config. This is essentially a kind of explicit management of state transfer and deactivation from old configs to new configs, albeit one that relies on a separate external master. So, in some sense, it still doesn’t fix the underlying problem of a state machine reconfiguration itself, but arguably has a clearer separation of concerns.

### 5.5 Fast Paxos

Classic Paxos takes 2 round trips to get a value committed (1 for the *Prepare* phase and 1 for the *Commit* phase). How could we do better than this? Fast Paxos [Lam06] makes this improvement by having clients send their proposals directly to acceptors, rather than going through proposers first. This also changes quorum requirements, though. TODO.

### 5.6 Egalitarian Paxos

Egalitarian Paxos (EPaxos) [MAK13] goes further by trying to achieve a leaderless scheme while also allowing for fast path commits. It relaxes notion of strict ordering between

command slots by tracking only dependency between commands explicitly, and executing commands only when they are committed, and in accordance with this dependency order.

## 5.7 Zab

Zab [JRS11, RJ08] is a crash-recovery atomic broadcast algorithm used in Apache Zookeeper. The protocol consists of two main modes: *broadcast* and *recovery*.

In a stable system, it should be in broadcast mode, where a single leader is broadcasting transaction messages to a quorum of synchronized followers, until the leader fails or it no longer has a quorum of followers. Leaders will broadcast a proposal for a message to be delivered, and before doing this will assign a monotonically increasing unique id, the *zxid*. Delivered messages will be ordered by their *zxids*. When a leader receives ACKs from a quorum, the leader will broadcast a COMMIT message and deliver the message locally.

When the service starts or a leader fails, the system enters into recovery mode. Recovery and leader election is needed to ensure liveness in the face of leader failure. In a standard implementation *zxids* are 64-bit numbers where the lower 32 bits are a simple counter, and the higher order 32 bits are the epoch. The epoch is incremented by a new leader to something greater than the highest epoch it has seen, and then the counter is reset to zero. If the leader election protocol guarantees that the new leader has the highest proposal number in a quorum of servers, a newly elected leader will also have all committed messages.

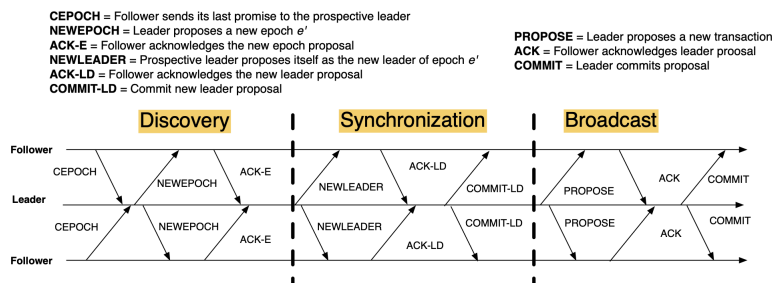


Fig. 5. Zab protocol summary

Can see a TLA+ formal specification of the high level Zab protocol here, which is a part of the official Apache Zookeeper repo.

## 6 Byzantine Fault Tolerance

The earliest explicit reference to *Byzantine* faults appeared in [LSP82], though earlier work had touched on the same problem without referring to it by that moniker [PSL80, WLG<sup>+</sup>78]. They show in [LSP82] that when using “oral” messages (i.e. non-signed) messages, a Byzantine agreement solution requires  $3f + 1$  processes, even in a synchronous communication model. They give an algorithm that solves the problem assuming  $n > 3f + 1$ , and also show that if we allow for “written” (e.g. digitally signed) messages, then in the synchronous model Byzantine agreement can be achieved with only  $f + 1$  processes.

### 6.1 Model

The work on Practical Byzantine Fault Tolerance (PBFT) [CL99] considers an asynchronous distributed system where nodes are connected by a network which can fail to deliver messages, delay them, or deliver them out of order. Furthermore, it allows for *Byzantine* faults i.e., faulty nodes may behave arbitrarily, subject only to the above restrictions. This model does assume, however, cryptographic techniques that prevent spoofing and can detect corrupted messages. That is, Byzantine processes may send any arbitrary message, but we assume the identity of the sender of a message can be determined by the receiver [Lam11]. This can be achieved this with public-key signatures [RSA78], message authentication codes (MACs), etc.

### 6.2 Intuitions and Algorithm

If we assume a starting point of a classic 2-phase Paxos consensus approach, the following are some of the essential issues that arise and must be dealt with when we add in Byzantine faults:

1. **Leader equivocation:** if a leader is faulty (Byzantine), then it can trivially send two conflicting messages in the same view (i.e. with the same proposal number). This

means that, for example, it could send out and accept messages with its own proposal number but with a different value to each replica. Then, we would end up with a quorum of replicas having accepted that proposal, but they all have different values, so which one is the true value to agree upon?

2. **Wrong value adoption:** A leader (faulty or not) that accepts a wrong value (i.e. not highest among previously) chosen can lead to safety violation as considered in the standard 2-phase Paxos model.

Need to have a way for honest acceptor to only accept values if they have actually have proof that

- If a leader/proposer is Byzantine, we can imagine it as not being a “useful” participant of the protocol, in that it may only be trying to be malicious. And, we can’t control its behavior anyways, so we really need to worry about how acceptors can protect themselves against malicious leaders.
- Normally, without Byzantine faults, acceptors can assume any incoming messages from proposers are legit, and they can respond with promises or acceptances accordingly.
- With Byzantine faults, though, the info they would hear from a proposer can’t be trusted. So, can we force acceptors to somehow be more stringent in their acceptance of messages from proposers? In order to ensure they only actually accept messages from honest proposers?
- In essence, have proposers record the info they received from a large enough set of honest acceptors, in order to prove to an acceptor that this info was collected. Basically, let acceptors require that proposers prove to them that they collected info about prior acceptances from enough honest acceptors. Since we assume no forging possible we can have acceptors sign info accordingly in a way that proves they actually had a certain piece of info.
- **Point:** Acceptors will only accept if they have proof in the accept message that  $X$  number of honest acceptors stored a particular proposal.
- So, proposers first try to do their proposals by asking around acceptors, from which they receive promises. Then, the proposer sends out another round of “real” proposer

The essence of the algorithm is as follows:

1. Primary sends a *PrePrepare*(*value*, *p*) message for view/proposal number *p*.
2. Replica responds to the first *PrePrepare* message it receives from a primary.
3. Primary gathers *PrePrepare* responses from  $n - f$  replicas, and then sends *Prepare*(*v*, *proof*) (note this message may be linear in size since it contains signed codes from up to  $n$  nodes.)
4. If a replica sees *Prepare*(*value*, *p*, *proof*) and *proof* contains  $n - f$  valid signatures for *PrePrepare*(*value*, *p*), then it goes ahead and accepts.
5. Primary then gathers  $n - f$  *Prepare* responses from replicas.

Note that since we assume a public key infrastructure (PKI) set up between nodes of the system, any node can securely verify that a message was signed by some other node.

## From Classic Paxos to Byzantine

In Classic Paxos, we can think about  $2a$  messages being sent to acceptors as a record of the proposer gathering some information about that proposal in phase 1: namely, that a quorum of acceptors promised to prepare in that round/ballot, and never accept proposals from earlier rounds. In a Byzantine setting, we can’t rely on a proposer/leader as an aggregator of this information, since a Byzantine leader can lie about any of this info. So, fundamentally, to achieve the same guarantees that we need before executing  $2a$  messages in Classic Paxos, acceptors need to gather this information themselves, by simply broadcasting message queries to all other nodes and gathering responses.

If an acceptor can gather enough responses ( $2f$ ) that other acceptors were prepared for a given proposal/round, then they can consider the proposal as accepted, and advance to learning/commit phase. If we assume at most  $f$  failures and  $3f + 1$  acceptors, then if we get confirmation of  $2f + 1$  prepares, we know that...?

### 6.3 Notes

- Given  $n = 3f + 1$  nodes, for any 2 quorums with  $n - f = 2f + 1$  nodes, we are guaranteed they intersect in at least  $f + 1$  nodes (just draw a picture). Note that if you talk to at least  $f + 1$  nodes then you are sure you are in contact with at least one non-faulty (non-Byzantine) node.

## 7 Blockchain and Cryptocurrency

Decentralized currency have become a popular peer to peer consensus systems that operate under significantly different assumptions and fault models than previous systems.

### 7.1 Bitcoin

Bitcoin [Nak09] is the first widely used decentralized cryptocurrency. Nodes participate in a peer-to-peer network that implements a distributed ledger which records all transactions between parties, which can be uniquely identified using cryptographic keys (e.g. RSA private keys). The ledger can be viewed as a type of database, consisting of a series of blocks that record transactions on the database. The current state of the database can be considered as the state of the ledger after applying all transactions in the ledger.

Generally, we can view our current (or most any) money system as, more or less, a big old database. As Buterin states in [But14]:

... all a currency, or token system, fundamentally is is a database with one operation: subtract  $X$  units from  $A$  and give  $X$  units to  $B$ , with the proviso that:

- (1)  $A$  had at least  $X$  units before the transaction.
- (2) The transaction is approved by  $A$ .

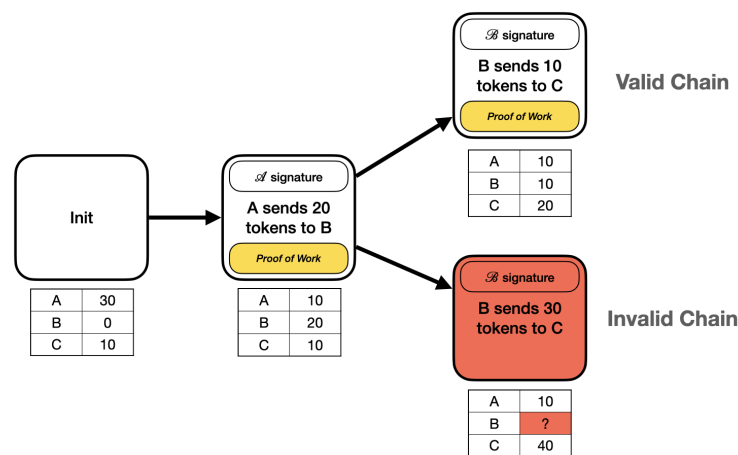
Every user/client of the database can have an account in this database, which records the current amount of money in their account (i.e. “wallet”). Transactions are then executed by atomically transferring money from one account to another, by deducting some amount  $X$  from user  $A$ ’s account and adding  $X$  to user  $B$ ’s account, with the restriction that  $A$  cannot send  $X$  dollars to some other account if it does not have at least  $X$  dollars. And, the transaction that completes between two accounts must occur atomically (consistently), before any other transactions take place. That is, we can think about all transactions as being serialized into a big list of transactions, which make up the *ledger* or *history* of the database. More generally, we can also consider this ledger itself as the current state of the database, since this state can always be computed by simply applying all transactions from the beginning of the ledger. We also might assume that there may be some special entries in this ledger that put new money into circulation by giving it to some account without requiring it to be transferred from an existing account.

If you try to build a money system on this decentralized ledger/database model, you have the obvious initial problem of how we update the database consistently and safely without the use of some central trusted authority. We can imagine that everyone has a copy of the full ledger, and can choose to make arbitrary updates to it locally e.g. even ones that break the *no double spending* consistency property i.e., people could arbitrarily choose to spend money they don’t have, breaking property 1 above. Additionally, we can assume that each party in the network can be uniquely identified by some cryptographic signing scheme e.g., each by their unique, private RSA key. They can mark a transaction between themselves, party  $A$  and another user, party  $B$ , by referring to the public key of  $B$  and signing the transaction with  $A$ ’s private key. Based on this, other parties can then verify that  $A$  was indeed the one who sent some money to  $B$ .

If everyone is updating their forks of the ledger independently, though, each with some potentially unsafe transactions, how do we enforce safety in a distributed fashion? Well, we must assume that there are at least some amount of honest nodes in the network that want to do good i.e., they are actually honest in wanting to only make sure that valid chains are kept in the system. Under this assumption, we can then use some mechanism that allows the honest agents to “outvote” the bad players when deciding on the correctness of the ledger. This can be implemented with the *proof of work* concept.

Basically, we imagine appending a special *nonce* to each transaction, such that the original transaction concatenated with this nonce makes up the full transaction that goes into the chain. In order for a transaction to be valid, though, we require some property of the hashed block to be true that is computationally hard to invert. For example, by requiring that the SHA-256 hash of the original block plus the nonce starts with some number of zero bits. If this property holds true, then the transaction/block is considered valid, and this means fiddling with the data of the transaction would be computationally hard, since you would

have to re-solve for a valid nonce. So, this implicitly ensures that votes are given to those with CPU power, and so if enough CPUs are “honest”, then we have a good guarantee that honest nodes will win out in selecting the true ledger.



In order to make a block “valid”, you have to sign it with a special hash that is based on the block’s content, and is computationally hard to come up with. This is the *proof of work*. So, if you’ve sent out a valid block with a valid proof of work, it means you must have spent some amount of computational work on creating this block. This serves as the kind of “voting” power, allowing the larger pool of computational resources in the network to outvote any minority of bad actors, since, on average, this larger pool will win out in creating valid blocks and extending their chain.

## 7.2 Ethereum

Ethereum, originally published in a whitepaper [But14] in 2014 by Vitalik Buterin, is a newer alternative to Bitcoin that is based on similar ideas and goals. Most notably, it introduces an explicit way to implement *smart contracts* within the Ethereum blockchain, which allows for more elaborate financial contracts and transactions to be carried out between parties in the system. This can be viewed as a kind of generalization of the basic banking *state transition model* of Bitcoin, that only allowed users to send value between each other without more complex contractual logic determining rules on how value can flow between parties.

In Ethereum, the global system state is made up of objects called *accounts*, which are each identified by a 20-byte address. *Transactions* are direct transfers of value and information between accounts. An Ethereum account contains four fields:

1. **nonce**: a counter to ensure transactions are processed once.
2. **ether balance**: the current balance of the account.
3. **contract code**: if present.
4. **storage**: which is empty by default.

and there two different types of accounts:

- **Externally owned accounts**: controlled by private keys. These accounts have no code, and you can send messages from such an account by creating and signing a transaction.
- **Contract accounts**: controlled by their contract code. In these accounts, every time the contract account receives a *message* its code activates, allowing it to read and write to internal storage, send other messages, or create new contracts.

### 7.2.1 Messages and Transactions

A *message* in Ethereum is similar to a “transaction” in Bitcoin, but differs in that an Ethereum message can be created either by an external entity or by a contract, whereas a Bitcoin transaction can only be created externally. There is also an explicit option for Ethereum messages to contain data. Finally, the recipient of an Ethereum message, if it is a contract account, has the option to return a response, which means that Ethereum messages also encompass the concept of functions.

*Transactions* in Ethereum contain the recipient of the message, a signature identifying the sender, the amount of ether and the data to send, as well as two values called *STARTGAS* and *GASPRICE*. To prevent exponential blowup and infinite loops in execution of contract code, each transaction is required to set a limit to how many computational steps of code execution it can spawn, including both the initial message and any additional messages that get spawned during execution. *STARTGAS* is the limit on computational steps, and *GASPRICE* is the fee to pay to the miner per computational step.

### 7.3 Blockchain Oracles

Although smart contracts allow for secure, decentralized policies to be implemented within a blockchain network (e.g. in Ethereum) it is often the case that these contracts may want to use data sources that come from the outside world (e.g. stock stickers, weather, etc.). Mechanisms are needed for pulling in this data in a secure fashion, so that the security of the underlying contract is not compromised in cases where the external data source may also be compromised. A *blockchain oracle* [ZCC<sup>+</sup>16, BCC<sup>+</sup>21] is a third party service that connects a smart contract with the outside world, in an effort to address this issue.

Some of these oracle systems [ZCC<sup>+</sup>16] rely on running partially inside trusted execution environments, like Intel SGX.

## References

- [ADD<sup>+</sup>19] Ittai Abraham, Srinivas Devadas, Danny Dolev, Kartik Nayak, and Ling Ren. Synchronous byzantine agreement with expected  $o(1)$  rounds, expected communication, and optimal resilience. In *Financial Cryptography and Data Security: 23rd International Conference, FC 2019, Frigate Bay, St. Kitts and Nevis, February 18–22, 2019, Revised Selected Papers*, page 320–334, Berlin, Heidelberg, 2019. Springer-Verlag.
- [AH90] James Aspnes and M. Herlihy. Fast randomized consensus using shared memory. *J. Algorithms*, 11(3):441–461, sep 1990.
- [BBC<sup>+</sup>11] Jason Baker, Chris Bond, James C. Corbett, JJ Furman, Andrey Khorlin, James Larson, Jean-Michel Leon, Yawei Li, Alexander Lloyd, and Vadim Yushprakh. Megastore: Providing scalable, highly available storage for interactive services. In *Conference on Innovative Data Systems Research (CIDR)*, pages 223–234, 2011.
- [BCC<sup>+</sup>21] Lorenz Breidenbach, Christian Cachin, Benedict Chan, Alex Coventry, Steve Ellis, Ari Juels, Farinaz Koushanfar, Andrew Miller, Brendan Magauran, Daniel Moroz, et al. Chainlink 2.0: Next steps in the evolution of decentralized oracle networks. *Chainlink Labs*, 1:1–136, 2021.
- [BHG86] Philip A Bernstein, Vassos Hadzilacos, and Nathan Goodman. *Concurrency control and recovery in database systems*. Addison-Wesley Longman Publishing Co., Inc., USA, 1986.
- [BP16] Carlos Baquero and Nuno Preguiça. Why logical clocks are easy: Sometimes all you need is the right language. *Queue*, 14(1):53–69, February 2016.
- [But14] Vitalik Buterin. Ethereum White Paper: A Next Generation Smart Contract & Decentralized Application Platform. 2014.
- [CBG15] Andrea Cerone, Giovanni Bernardi, and Alexey Gotsman. A Framework for Transactional Consistency Models with Atomic Visibility. In Luca Aceto and David de Frutos Escrig, editors, *26th International Conference on Concurrency Theory (CONCUR 2015)*, volume 42 of *Leibniz International Proceedings in Informatics (LIPIcs)*, pages 58–71, Dagstuhl, Germany, 2015. Schloss Dagstuhl – Leibniz-Zentrum für Informatik.
- [CDE<sup>+</sup>12] James C Corbett, Jeffrey Dean, Michael Epstein, Andrew Fikes, Christopher Frost, Jeffrey John Furman, Sanjay Ghemawat, Andrey Gubarev, Christopher Heiser, Peter Hochschild, et al. Spanner: Google’s Globally Distributed Database. *ACM Transactions on Computer Systems (TOCS)*, 31(3):1–22, 2012.
- [CL99] Miguel Castro and Barbara Liskov. Practical byzantine fault tolerance. In *Proceedings of the Third Symposium on Operating Systems Design and Implementation*, OSDI ’99, page 173–186, USA, 1999. USENIX Association.

- [CPAC17] Natacha Crooks, Youer Pu, Lorenzo Alvisi, and Allen Clement. Seeing is believing: A client-centric specification of database isolation. In *Proceedings of the ACM Symposium on Principles of Distributed Computing*, PODC '17, page 73–82, New York, NY, USA, 2017. Association for Computing Machinery.
- [Fid88] C. J. Fidge. Timestamps in message-passing systems that preserve the partial ordering. *Proceedings of the 11th Australian Computer Science Conference*, 10(1):56–66, 1988.
- [Her91] Maurice Herlihy. Wait-free synchronization. *ACM Trans. Program. Lang. Syst.*, 13(1):124–149, jan 1991.
- [JHKM24] Chris Jensen, Heidi Howard, Antonios Katsarakis, and Richard Mortier. Unanimous 2pc: Fault-tolerant distributed transactions can be fast and simple. In *Proceedings of the 11th Workshop on Principles and Practice of Consistency for Distributed Data*, PaPoC '24, page 44–57, New York, NY, USA, 2024. Association for Computing Machinery.
- [JRS11] Flavio P. Junqueira, Benjamin C. Reed, and Marco Serafini. Zab: High-performance broadcast for primary-backup systems. In *Proceedings of the 2011 IEEE/IFIP 41st International Conference on Dependable Systems&Networks, DSN '11*, page 245–256, USA, 2011. IEEE Computer Society.
- [KPF<sup>+</sup>13] Tim Kraska, Gene Pang, Michael J. Franklin, Samuel Madden, and Alan Fekete. Mdcc: multi-data center consistency. In *Proceedings of the 8th ACM European Conference on Computer Systems*, EuroSys '13, page 113–126, New York, NY, USA, 2013. Association for Computing Machinery.
- [Lam01] Leslie Lamport. Paxos made simple. *ACM SIGACT News (Distributed Computing Column)* 32, 4 (Whole Number 121, December 2001), pages 51–58, 2001.
- [Lam06] Leslie Lamport. Fast paxos. *Distributed Computing*, 19:79–103, October 2006.
- [Lam11] Leslie Lamport. Byzantizing paxos by refinement. In *Proceedings of the 25th International Conference on Distributed Computing*, DISC'11, page 211–224, Berlin, Heidelberg, 2011. Springer-Verlag.
- [LMZ09] Leslie Lamport, Dahlia Malkhi, and Lidong Zhou. Vertical paxos and primary-backup replication. In *Proceedings of the 28th ACM symposium on Principles of distributed computing*, pages 312–313, 2009.
- [LSP82] Leslie Lamport, Robert Shostak, and Marshall Pease. The Byzantine Generals Problem. *ACM Trans. Program. Lang. Syst.*, 4(3):382–401, jul 1982.
- [MAK13] Iulian Moraru, David G. Andersen, and Michael Kaminsky. There is more consensus in egalitarian parliaments. In *Proceedings of the Twenty-Fourth ACM Symposium on Operating Systems Principles*, SOSP '13, page 358–372, New York, NY, USA, 2013. Association for Computing Machinery.
- [Nak09] Satoshi Nakamoto. Bitcoin: A peer-to-peer electronic cash system. May 2009.
- [PD10] Daniel Peng and Frank Dabek. Large-scale incremental processing using distributed transactions and notifications. In *Proceedings of the 9th USENIX Conference on Operating Systems Design and Implementation*, OSDI'10, page 251–264, USA, 2010. USENIX Association.
- [PSL80] M. Pease, R. Shostak, and L. Lamport. Reaching agreement in the presence of faults. *J. ACM*, 27(2):228–234, apr 1980.
- [RJ08] Benjamin Reed and Flavio P. Junqueira. A simple totally ordered broadcast protocol. In *Proceedings of the 2nd Workshop on Large-Scale Distributed Systems and Middleware*, LADIS '08, New York, NY, USA, 2008. Association for Computing Machinery.
- [RSA78] R. L. Rivest, A. Shamir, and L. Adleman. A method for obtaining digital signatures and public-key cryptosystems. *Commun. ACM*, 21(2):120–126, feb 1978.
- [SPAL11] Yair Sovran, Russell Power, Marcos K. Aguilera, and Jinyang Li. Transactional storage for geo-replicated systems. In *Proceedings of the Twenty-Third ACM Symposium on Operating Systems Principles*, SOSP '11, page 385–400, New York, NY, USA, 2011. Association for Computing Machinery.

- [TDW<sup>+</sup>12] Alexander Thomson, Thaddeus Diamond, Shu-Chun Weng, Kun Ren, Philip Shao, and Daniel J. Abadi. Calvin: fast distributed transactions for partitioned database systems. In *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, SIGMOD '12, page 1–12, New York, NY, USA, 2012. Association for Computing Machinery.
- [WLG<sup>+</sup>78] J.H. Wensley, L. Lamport, J. Goldberg, M.W. Green, K.N. Levitt, P.M. Melliar-Smith, R.E. Shostak, and C.B. Weinstock. Sift: Design and analysis of a fault-tolerant computer for aircraft control. *Proceedings of the IEEE*, 66(10):1240–1255, 1978.
- [ZCC<sup>+</sup>16] Fan Zhang, Ethan Cecchetti, Kyle Croman, Ari Juels, and Elaine Shi. Town crier: An authenticated data feed for smart contracts. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, CCS '16, page 270–282, New York, NY, USA, 2016. Association for Computing Machinery.
- [ZSS<sup>+</sup>15] Irene Zhang, Naveen Kr. Sharma, Adriana Szekeres, Arvind Krishnamurthy, and Dan R. K. Ports. Building consistent transactions with inconsistent replication. In *Proceedings of the 25th Symposium on Operating Systems Principles*, SOSP '15, page 263–278, New York, NY, USA, 2015. Association for Computing Machinery.