Thespis: Actor-Based Middleware for Causal Consistency

Carl Camilleri¹, Dr. Joseph Vella², Dr. Vitezslav Nezval³,
¹University of Malta, Computer Information Systems, Faculty of ICT
Computer Building, University of Malta, Msida, Malta
carl.camilleri.04@um.edu.mt
² University of Malta, Computer Information Systems, Faculty of ICT
Computer Building, University of Malta, Msida, Malta
joseph.g.vella@um.edu.mt
³ University of Malta, Computer Information Systems, Faculty of ICT
Computer Building, University of Malta, Msida, Malta
vitezslav.nezval@um.edu.mt

Abstract: This paper provides a survey of the current state of the art in Causally-Consistent data stores. Furthermore, we present the design of Thespis, a middleware that innovatively leverages the Actor model to implement causal consistency over an industry-standard data store.

Keywords: causal consistency, distributed databases, actor model, middleware

1. Introduction

The CAP theorem [4] proves [10] that having both Availability and Partition Tolerance within data stores that implement Strong Consistency [11] is not possible. The latter consistency model, also known as Sequential Consistency, is the strongest type of consistency offered by traditional database management systems.

The rise of cloud-oriented, distributed infrastructures has led to a wide adoption of data stores that forego strong data consistency in favour of availability and partition tolerance, to provide the performance, scalability and high-availability properties sought by enterprise-scale online applications. Popular data stores in this area offer Eventual Consistency [21], a weak consistency model which guarantees that, given no new write operations, all nodes of the data stores eventually converge to the same state.

Although Eventual Consistency is relatively easy to achieve, developing applications against such a weak consistency model is regularly problematic, and shifts data safety and consistency responsibilities, traditionally handled implicitly by the data storage layer, to the application layer [8].

Causal Consistency [2] is weaker than Sequential Consistency, but stronger than Eventual Consistency, and has in fact been proven to be the strongest type of consistency that can be achieved in a fault-tolerant, distributed system [17].

Informally, Causal Consistency implies that readers cannot find a version of a data element before all the operations that led to that version are visible [3].

2. Literature Survey

2.1 Definitions

Causal Consistency. A system is causally consistent if all operations that are causally related are seen in the same order across all the nodes in the distributed data store [2]. Two operations $a$ and $b$ are deemed to be potentially causally-related, denoted by $a \rightarrow b$, under three criteria [15]:

1. **Thread of Execution**: Given a process $P$, operations within the same process are causally-related. In other words, $a \rightarrow b$ if $P$ performs $a$, then performs $b$
2. **Reads from**: Given a write operation $a$, if $b$ reads the result of $a$ then $a \rightarrow b$
3. **Transitivity**: If $a \rightarrow b$ and $b \rightarrow c$, then $a \rightarrow c$

Conflict Handling. For a distributed data store to provide high-availability and low latency, state changes need to be accepted at any replica of the data store without requiring co-ordination, at least in the critical path, with other replicas [3].

A state of conflict is declared when the same data item, in two different replicas, gets updated concurrently. Two operations on the same key are conflicting if they write a different value, and are not related by causality [2].

Formally, given two operations $\Theta_1$ and $\Theta_2$ on a data item defined by key $k$:

- $\Theta_1 = \text{put}(k,v_1)$
- $\Theta_2 = \text{put}(k,v_2)$
- $\Theta_1$ and $\Theta_2$ and $\Theta_1$ are concurrent

A number of approaches for conflict detection and conflict resolution have been put forward ([5], [20], [14]), with a popular one being the Last-Writer Wins (LWW), where the latest update is assumed to be the valid value.
A data-store which offers causal consistency, as well as conflict detection and resolution, is referred to as a system that provides causal+ consistency [16].

3. Thespis Approach

We describe the design of Thespis, a middleware that provides causal+ consistency whilst storing data in data stores which, out of the box, offer a) a strong consistency model; and b) no support for horizontal scalability. This fits the description of a RDBMS. Relational databases are widely used in production systems, and offer a rich data model with powerful querying capabilities. Hence, although not mandatory to our approach, the rest of this paper assumes that: a) the main backing data store is a relational database; and b) that the client is an application handling “objects”, primarily instances of business-domain models.

3.1 Concepts

Actor Model. In the Actor model [12], logic is modelled in terms of a hierarchical society of “experts”, that communicate together via asynchronous message passing. An actor consists of: a) a mailbox where incoming messages are queued; b) actor behaviour logic, which determines what logic should be executed in response to a received message; and c) actor state, data which describes the state of the actor at a given point in time. Actors process one message at a time, and exist in the context of Actor Systems [1], where hierarchies can form.

Command Query Responsibility Segregation (CQRS). CQRS [22] is a software design pattern that applies the concept of Command Query Separation (CQS) [18] in order to maintain separate data models for queries (or READ operations) and commands (or WRITE operations)

Event Sourcing (ES). ES [9] is another software architectural pattern where all data changes are captured as a sequence of events that are stored in an event log and that, when applied in order, provide a view of the system state at a particular point in time.

3.2 System Model

Our middleware needs to deal with concurrency. At the very least, each instance of an object can have a number operations performed on it. The two types of basic operations are Read and Write operations. Read operations can happen concurrently, whereas Write operations on the same object, in the same data centre, need to happen sequentially.

In our system model, we adopt the Actor model to handle concurrency. Furthermore, we also exploit the hierarchical nature of Actor Systems in order to reflect a causally-consistent view of the underlying data store. The middleware design, as illustrated in Figure 1, is comprised of four main components:

1. A Persistent Business-Model Actor System. This actor system holds a set of actors which can provide a view of the underlying data store to the application. The business-model actor system encapsulates:
   a. One actor per entity. In the first concept, we define this as being one entity per type of business object being dealt with.
   b. One actor per instance, supervised by the relevant entity actor. Each business object being dealt with by the application (and/or loaded from the underlying database) is assigned to a specific actor. The state of the Entity Instance Actor is made up of two important elements, namely the Entity Instance and the Event Log. The events in the Event Log can be applied to the Entity Instance in order to retrieve the latest (causally-consistent) version of the entity

2. A Persistence Actor, responsible for persisting actor states within the underlying data store
3. A Reader Actor, responsible for retrieving business objects from the underlying data store
4. A Replication Actor, responsible for replicating actor state changes from one data centre to the other

![Figure 1 - System Model](image-url)

3.3 Event-Sourced Data Persistence

Our design adopts a variant and combination of the CQRS and the Event-Sourcing patterns, where:

1. Data changes are snapshotted in the backing data store only when it has been received, at middleware layer, in all the data centres
2. Commands (i.e. write operations) are captured in the middleware layer. Given a new version of any entity, a set of events representing the new state, compared to the previous version, are extracted
3. The events representing the new state are persisted in the local data centre, and asynchronously replicated to other data centres.
4. Upon creation of an Entity Instance Actor (i.e. the first time that an instance is being read), two READ operations are done:
a. The first read operation gets the entity from the primary database location
b. The second read operation gets any events that have occurred on the given entity
5. Any events occurring on the given entity that have not yet been applied to the version of the entity in the primary database location, but would still yield a causally-consistent version, are applied and stored in the state of the Entity Instance Actor
6. Any subsequent READ operations on the same entity can therefore return the entity immediately
7. Any WRITE operations on the entity result in two operations:
   a. The set of events that describe a move from the current version to the new version are inferred. Events basically dictate which properties of an entity were updated. These events are persisted in the event store and sent for replication.
   b. The state of the Entity Instance actor is updated with the new version. This therefore means that any subsequent reads from any client in the same data centre will get the new version, and guarantees read-your-writes consistency from the same client.

### 3.4 Event Logging

Data changes are described as Write Events and stored in an Event log. A Write event in the log consists of:
1. EvtID, an event identifier, unique in the originating data centre
2. EID, the Entity identifier to which it relates
3. ETYP, the type of entity to which the event relates
4. SID, the identifier of the server where the event happened
5. TS, a timestamp describing the point in time when the event happened
6. Data, a set of <key,value> pairs that define the new values of the entity’s properties

### 3.5 Replication and Stabilisation Protocol

The replication protocol in our design is founded on the Actor model and employs two algorithms. Algorithm 1 runs on the Originating Server, in other words the server where a new event is created. On the other hand, Algorithm 2 runs on the Remote Server, or the server which is receiving an event from an Originating Server.

Key to the replication protocol, and to enforce causality, is the Stable Version Vector (SVV). The SVV is simply a vector of length $M$, the number of peer data centres. Each element $SV_{DC}$ in the vector is the latest observed timestamp from the corresponding peer data centre.

---

| Algorithm 1 – Originating Server Event Replication |
|--------------------------------------------------|
| 1. Load a set consisting of LOCAL EVENTS x PEERS, ordered in ascending order of timestamp. Each element of the set is a local event that has not been replicated to a remote DC |
| 2. For each element in the set: |
|   a. Spawn a remote child actor |
|   b. Send the event to the child actor |
|   c. Receive the acknowledgement that the event has been replicated to remote server DC |

| Algorithm 2 - Remote Server Event Replication |
|----------------------------------------------|
| 1. Add the event to the Event Log |
| 2. Update $SV_{DC}$ with the timestamp of the received message |
| 3. Acknowledge success to the originating DC |

### 3.8 Causality+ Correctness

The design of Thespis incorporates a small amount of meta-data, stored with each event, and a replication and stabilisation protocol in order to ascertain causal consistency across all nodes, as well as a LWW conflict resolution technique.

The type of meta data stored and the stabilisation protocols are similar to approaches that ascertain causality already found in the literature ([7], [6], [19]) however, we illustrate in this section, with a few examples, how the Thespis approach enforces causal consistency, as defined in Section 2.1.

**Thread of execution** is guaranteed by the fact that clients are always assigned to the same data centre, and the actor-based approach is providing a sequentially-consistent view of each data element. Therefore, at process/session level, the Thespis approach is providing a stricter consistency level

**Reads from** is guaranteed by the fact that a Read operation reads events that have either happened locally, or have been propagated across all servers. In other words, our approach favours an approach where data can be potentially stale to enforce causality, without losing “read-your-writes” guarantees.

**Transitivity** is also guaranteed by the replication and stabilisation protocol. Events are propagated sequentially (as guaranteed by the Actor model) and therefore, if an event has been propagated to all data centres (and is therefore available for clients), all its dependencies are necessarily already stable. In other words, a client cannot read an event before it can read all the events that have led to its occurrence.

Finally, LWW conflict resolution is also provided implicitly in our replication protocol. Given two conflicting WRITE operations on the same entity and on the same property, the
most recent entry in the event log overrides the conflicting version, resulting in the last-writer-wins resolution.

3.4 Event Timestamping

The design of Thespis requires a timestamping implementation that is able to differentiate, deterministically and unconditionally, whether an event has happened before or after another event.

A number of timestamping approaches are supported, including Physical Time, Logical Time [15] and Hybrid Logical Time [13]. We believe that event timestamping using Hybrid Logical Clocks most fits the Thespis approach, and this is supported also by conclusions in concurrent work ([6],[19]).

4. Conclusion

We have presented the design of Thespis, a middleware that guarantees causal consistency, and allows a data store with no in-built horizontal scalability or data multi-versioning capabilities to be deployed in a geo-located setup.

We have focused our efforts on the horizontal scalability of RDBMSs, a widely-deployed data storage solution for enterprise-class applications. Up to our knowledge, this is a novel approach in the study of causally-consistent data storage, as a number of works in this field focus on key-value data stores ([6],[16],[7]), or provide causal consistency over an eventually-consistent data store ([3]).

We have also founded our approach on firm software engineering principles and patterns, most prominently the Actor model, in itself a mathematical model describing a way to perform concurrent computation.

This, together with CQRS and ES, is also a novel approach to the implementation of a causally-consistent middleware: up to our knowledge, this is the first proposal where the Actor model has been uplifted to handle the idiosyncrasies of concurrency that a middleware such as ours needs to cope with, and we can also find no reference in the literature where the CQRS and ES patterns have been specifically employed to describe events happening in a causally-consistent data middleware.

5. Future Scope

Our next steps include the implementation of Thespis, and the implementation of real-world scenarios that can illustrate the usefulness of our approach. Secondly, the implementation of Thespis will allow us to benchmark the implementation against a stand-alone RDBMS setup, and also measure how variations in the replication protocols, as well as the in the event timestamping approach, can improve the degree of data freshness, and reduce the latency in the propagation and visibility of changes to remote clients.

6. References

[1] Gul A Agha. Actors: A model of concurrent computation in distributed systems. Technical report, DTIC Document, 1985.
[2] Mustaque Ahamad, Gil Neiger, James E Burns, Prince Kohli, and Phillip W Hutto. Causal memory: Definitions, implementation, and programming. *Distributed Computing*, 9(1):37–49, 1995.
[3] Peter Bailis, Ali Ghodsi, Joseph M Hellerstein, and Ion Stoica. Bolt-on causal consistency. In *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data*, pages 761–772. ACM, 2013.
[4] Eric A Brewer. Towards robust distributed systems. In *PODC*, volume 7, 2000.
[5] 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):8, 2013.
[6] Diego Didona, Kristina Spirovskva, and Willy Zwaenepoel. Okapi: Causally consistent geo-replication made faster, cheaper and more available. arXiv preprint arXiv:1702.04263, 2017.
[7] Jiaying Du, Călin Iorgulescu, Amitabh Roy, and Willy Zwaenepoel. GentleRain: Cheap and scalable causal consistency with physical clocks. In *Proceedings of the ACM Symposium on Cloud Computing*, pages 1–13. ACM, 2014.
[8] Mawahib Musa Elbushra and Jan Lindström. Eventual consistent databases: State of the art. *Open Journal of Databases (OJDB)*, 1(1):26–41, 2014.
[9] Martin Fowler. Event sourcing. https://martinfowler.com/eaadDev/EventSourcing.html, December 2005.
[10] Seth Gilbert and Nancy Lynch. Brewer’s conjecture and the feasibility of consistent, available, partition-tolerant web services. *ACM SIGACT News*, 33(2):51–59, 2002.
[11] Maurice P. Herlihy and Jeannette M Wing. Linearizability: A correctness condition for concurrent objects. *ACM Transactions on Programming Languages and Systems (TOPLAS)*, 12(3):463–492, 1990.
[12] Carl Hewitt, Peter Bishop, and Richard Steiger. A universal modular actor formalism for artificial intelligence. In *Proceedings of the 3rd international joint conference on Artificial intelligence*, pages 235–245. Morgan Kaufmann Publishers Inc., 1973.
[13] Sandeep S. Kulkarni, Murat Demirbas, Deepak Madappa, Bharadwaj Avva, and Marcelo Leone. Logical physical clocks. In *International Conference on Principles of Distributed Systems*, pages 17–32. Springer, 2014.
[14] Avinash Lakshman and Prashant Malik. Cassandra: a decentralized structured storage system. *ACM SIGOPS Operating Systems Review*, 44(2):35–40, 2010.
[15] Leslie Lamport. Time, clocks, and the ordering of events in a distributed system. *Communications of the ACM*, 21(7):558–565, 1978.
[16] Wyatt Lloyd, Michael J Freedman, Michael Kaminsky, and David G Andersen. Don’t settle for eventual: scalable causal consistency for wide-area storage with cots. In *Proceedings of the Twenty-Third ACM Symposium on Operating Systems Principles*, pages 401–416. ACM, 2011.
[17] Prince Mahajan, Lorenzo Alvisi, and Mike Dahlin. Consistency, availability, and convergence. University of Texas at Austin Tech Report, 11, 2011.
[18] Bertrand Meyer. Eiffel: A language for software engineering. Department of Computer Science, University of California, 1986.
[19] Mohammad Roohitavaf and Sandeep Kulkarni. Gentlerain+: Making gentlerain robust on clock anomalies. arXiv preprint arXiv:1612.05205, 2016.
[20] Douglas B Terry, Marvin M Theimer, Karin Petersen, Alan J Demers, Mike J Spreitzer, and Carl H Hauser. Managing update conflicts in bayou, a weakly connected replicated storage system. In ACM SIGOPS Operating Systems Review, volume 29, pages 172–182. ACM, 1995.
[21] Werner Vogels. Eventually consistent. Communications of the ACM, 52(1):40–44, 2009.
[22] Greg Young. Cqrs documents by greg young, 2010.