Reliable Actors with Retry Orchestration

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Cloud developers have to build applications that are resilient to failures and interruptions. We advocate for a fault-tolerant programming model for the cloud based on actors, retry orchestration, and tail calls. This model builds upon persistent data stores and message queues readily available on the cloud. Retry orchestration not only guarantees that (1) failed actor invocations will be retried but also that (2) completed invocations are never repeated and (3) it preserves a strict happen-before relationship across failures within call stacks. Tail calls can break complex tasks into simple steps to minimize re-execution during recovery. We review key application patterns and failure scenarios. We formalize a process calculus to precisely capture the mechanisms of fault tolerance in this model. We briefly describe our implementation. Using an application inspired by a typical enterprise scenario, we validate the functional correctness of our implementation and assess the impact of fault preparedness and recovery on performance.

CCS Concepts:
• Software and its engineering → Software fault tolerance; Cloud computing; Concurrent programming languages;
• Computing methodologies → Distributed programming languages.

Additional Key Words and Phrases: distributed systems, actors, fault tolerance, workflows

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1 INTRODUCTION
Clouds are complex distributed systems with many components each with their own points of failure [Sharma et al. 2016; Vishwanath and Nagappan 2010]. Cloud developers have to build applications that are resilient to failures and interruptions or face the risk of downtime and data loss. Many cloud applications leverage existing cloud services. While some services like persistent data stores can help achieving fault tolerance, others offer no or weak fault tolerance guarantees. Naively composing such services can be disastrous.

∗Work done while employed by IBM; currently employed by AMD

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Distributed programming models often strive to achieve or get close to transparent fault-tolerance. Because of hardware failures or software errors, tasks can fail and data can be lost. To tolerate faults, distributed runtime systems have to retry failed tasks and rebuild lost data, typically from a checkpoint or a log. Transparent fault-tolerance therefore implies that making multiple attempts at running a task should not be observably different from running the task exactly once. As a result, many programming models require that tasks (or just unfinished tasks) have no observable side effects, or that retries of tasks do not repeat prior side effects. They may help by buffering side effects then atomically applying all side effects at task completion time. They may also attempt to deduplicate or roll back the side effects produced by retries. All of these approaches require tasks to have certain properties—task may be pure, stateless, deterministic, idempotent, reversible, etc.—and side effects to be managed by the runtime system.

In this work, we target applications built by composing existing cloud services and new code. We can decide a programming model for the new code and build a runtime system to bridge new and existing application components, but we cannot constrain existing components and their invocation. In general, we cannot assume or control much about the side effects of service invocations. Moreover, we observe that fault-tolerance, transparent or not, does not mean that faults should not affect the behavior of an application. For example, many applications make time-sensitive decision. If a decision is delayed for too long because of a fault, the outcome must be different. In short, we also cannot assume that the side effects of tasks will be the same with each execution attempt.

Because of this harsh reality, we believe a novel programming model for fault-tolerant distributed applications is needed. This programming model cannot achieve transparent fault-tolerance, as it cannot magically mask or undo side effects from failed tasks, and cannot coalesce side effects within or across retries. The goal of this programming model therefore must be to facilitate authoring fault recovery code.

In this work we introduce, formalize, and evaluate KAR: a novel programming model, methodology, and runtime system for building fault-tolerant cloud applications. KAR builds upon the actor programming model. Applications consist of invocations of actor methods, which we refer to as tasks for brevity. KAR makes the following contributions:

- KAR makes it easy to split complex tasks into sequences of simple tasks using tail calls, so as to minimize re-execution upon failure.
- KAR automates and orchestrates retries ensuring that not only are failed tasks retried, but also that successful tasks are never repeated.
- A strict happen-before relationship is enforced between attempts at executing a task transitively including all subtasks of this task (blocking nested invocations), so that the “past” never leaks into the “present”.
- KAR automatically persists pending task parameters and results into message queues but does not prescribe how to persist actor state or interface with external services.

Tail calls make the transition from one task to the next atomic, ensuring a failure never results in retrying both caller and callee. Moreover, consecutive invocations of the same actor retain the actor lock. KAR preserves the lock across failures ensuring that the interrupted chain is resumed first. Retry orchestration frees developers from implementing retries and reasoning about redundant or overlapping retries. At the developer’s discretion, non-failed subtasks of a failed task may be canceled if still pending, preempted if already running, or awaited if neither canceled nor preempted.

KAR does not assume that all application state is funneled into a common persistent store, with the luxury of transactions or atomic updates. On the contrary, KAR obeys the separation principle of microservice architectures. letting actors directly interface with data stores and stateful services.
KAR requires that there exists a mechanism to settle pending calls to external services, i.e. eliminate all pending calls by completing them, preempting them, canceling them before execution, or any combination thereof. This requirement may be satisfied for different services in different ways such as forcibly closing connections, killing processes, flushing queues, or waiting for quiescence or timeouts. Importantly, this requirement does not necessitate coordination across services. We refer to this requirement as “ascertainment” since external services must permit KAR to ascertain that pending calls have been settled. Ascertainment makes it possible to generalize the happen-before guarantee from tasks to service invocations by delaying retries until after settlement.

Ascertainment combined with tail calls and retry orchestration make it possible to productively compose actors and cloud services (fault-tolerant or not) into fault-tolerant applications as illustrated in Section 2 with a small example of an actor wrapping a key-value store and in Section 5 via a workflow drawn from an enterprise application.

Like Resilient X10 [Crafa et al. 2014; Grove et al. 2019], KAR automatically preserves ordering dependencies across failures but unlike X10 it automatically retries failed tasks. Like Durable Functions [Burckhardt et al. 2021], given deterministic tasks KAR can produce deterministic outcomes irrespective of failures. But unlike Durable Functions, KAR does not require orchestration functions to be deterministic. Like Reliable State Machines [Mukherjee et al. 2019], KAR relies on reliable message queues to connect application components and build a replay-able log, but unlike Reliable State Machines, KAR permits applications to persist state outside of this log. Popular distributed actor runtimes like Akka [Akka 2011] and Ray [Moritz et al. 2018] redeliver an invocation request to a failed actor as soon the actor has recovered. They permit the retried invocations to run concurrently with subtasks of the original invocation. At best, this overlap complicates analyzing logs, at worst it can cause subtle races and deadlocks. KAR eliminates this overlap.

The main contributions of this paper are:

- We introduce KAR (Section 2) and formalize the core semantics of KAR to precisely formulate and establish its fault tolerance guarantees (Section 3).
- We succinctly describe an implementation of KAR (Section 4) and an enterprise cloud application built using KAR (Section 5).
- We empirically validate the functional correctness of our implementation and assess the impact of fault preparedness and recovery on performance (Section 6).

2 PROGRAMMING MODEL

The KAR programming model is not tied to a specific programming language. In this section, we demonstrate KAR using JavaScript as the base language. So far we have developed KAR applications using JavaScript, TypeScript, Python, and Java.

KAR applications are made of actors. A Latch actor may be implemented by a JavaScript class:

```javascript
class Latch {
  async activate() { this.v = 0 }
  async set(v) { this.v = v }
  async get() { return this.v }
}
```

The state of an actor instance, this.v in this example, is meant to be private and only accessed through instance methods. The activate method essentially functions as a constructor. It is implicitly invoked by KAR at actor instantiation time. Because many programming languages have strong opinions about what constructors can and cannot do, we prefer this portable idiom to constructors.

An actor is identified by its type and a unique instance id. The actor.proxy method synthesizes a reference to an actor instance:
let ref = actor.proxy('Latch', 'myInstance')

Multiple invocations of `actor.proxy` with the same parameters synthesize equivalent references, i.e., references to the same actor instance. The `actor.proxy` method does not instantiate actors. Actors are instantiated implicitly when first invoked.

Actors methods are always invoked indirectly:

```
await actor.call(actor.proxy('Latch', 'myInstance'), 'set', 42)
```

This indirection makes it possible for the KAR runtime to persist and possibly retry invocation requests. It also abstracts away the application topology: the caller and callee may be running in different application components.

Because IOs in JavaScript are normally asynchronous and because actor methods are meant to be remotely invocable, we uniformly make every actor method `async` and `await` every call. The `async` and `await` keywords are JavaScript idiosyncrasies. The reader unfamiliar with these keywords is encouraged to just ignore them. The equivalent Java code would not have them.

Invocations using `actor.call` are blocking. The call returns the result from the callee. Non-blocking actor invocations are written:

```
await actor.tell(actor.proxy('Latch', 'myInstance'), 'set', 42)
```

This call only waits for the invocation request to be acknowledged by the KAR runtime but does not wait for a result.

Exceptions in `actor.call` are propagated from callees to callers where they may be caught. Exceptions in `actor.tell` are logged and discarded. KAR also supports `reminders`, i.e., time-delayed and possibly periodic variants of `actor.tell`.

### 2.1 Failures and Persistence

Actors can fail, at once losing the in-memory state of the instance and interrupting all the method invocations in progress. However, the parameters of queued method invocations including invocations in progress at the time of a failure are not lost, being automatically persisted by KAR. A failed actor is automatically recreated by KAR if invoked again whether because of a retried invocation or a novel invocation.

KAR offers a persistence API for actors to save their state.

```javascript
class PersistentLatch {
  async activate() { this.v = await actor.state.get(this, 'v') | 0 }
  async set(v) { this.v = v; await actor.state.set(this, 'v', this.v) }
  async get() { return this.v }
}
```

Because `activate` is called both on construction and reconstruction upon failure, it should restore the in-memory state of the instance from its persisted state if any, or if none initialize the instance state, loading 0 into `this.v` in this example.

Actors however are free to choose if, when, and how to persist their state. KAR’s retry orchestration guarantees are not predicated on the use of the builtin persistence API.

### 2.2 Nested Calls, Reentrancy, Retry Orchestration

Nested calls, i.e., blocking actor calls originating from an actor, must pass an extra `this` argument as the first parameter of the call, shifting other `actor.call` arguments to the right. The identity of the caller is required by the runtime to permit reentrancy and to correctly orchestrate retries.
Figure 1 shows the possible execution timelines for a nested call without failures (1) or with a single failure (2-7). A first actor method represented by a square calls a second method represented by a diamond. A line ending with an arrow depicts a complete execution of the task, whereas a star depicts a failure interrupting the task, and a stop sign an intentional preemption by the runtime.

A failure may hit the caller before the call, resulting in a retry of the caller (2). It may hit the callee only, resulting in a retry of the callee (3). A failure may also hit the caller while it is waiting for the callee (4-7). Scenarios (4-5) describe the possible recovery strategies for a failure only affecting the caller. In (4), the callee runs to completion, whereas in (5) the callee is preempted. Scenarios (6-7) describe the possible strategies for a joint failure. In (6), the caller is retried, eventually reinvoking the callee. In (7), the failed callee is retried first, then the caller as in (6). A failure may also hit the caller after placing the call but before the callee has started leading to a similar choice (omitted from the figure for brevity). KAR does not prescribe the choice of (4) vs. (5) or (6) vs. (7). We formalize all these options. Preempting a running task or canceling a pending task may or may not be feasible or desirable. In (4-7) as illustrated by the oblique dashed red line, KAR delays the retry of the caller waiting either for the callee to complete (4), to be preempted (5), to be known to have failed (6), or to be retried (7). In the absence of failures, a call stack is a single logical thread of execution. KAR ensures that the decision on the callee’s fate and possible execution always happen before the
retry of the caller to preserve this logic upon failure. This guarantee is critical for safe reentrancy. Consider what would happen if `main` fails after invoking `task`. Figure 2(a) depicts the executions allowed by KAR where happens before ensures that `main` will only start executing after `task` has completed. Figure 2(b) shows what could happen if `main` is retried without waiting, with `main` and `callback` now executing concurrently. Queuing `callback` to run later does not help as that would result in a deadlock when `task` is reinvoked by the retried `main`.

### 2.3 Tail Calls

Nested calls require precise handling from the runtime and careful thinking from the developer to account for the possible failure scenarios (3-7) when both invocations have been issued already, but neither has completed yet. However, if the invocation of the callee is the last thing the caller wants to do, we can replace the nested call (`actor.call`) with a tail call (`actor.tailCall`). In essence, a tail call simultaneously completes the caller’s invocation while issuing the invocation of the callee.

For instance, tail calls make it possible to reliably increment a counter in a key-value store with only `get` and `set` methods:

```javascript
class Accumulator {
    async get() { return await store.get('key') }
    async set(value) { await store.set('key', value); return 'OK' }
    async incr() {
        let value = await store.get('key')
        return await actor.tailCall(this, 'set', value+1)
    }
}
```

The `incr` method reads the value from the store then makes a tail call to the `set` method to store the incremented value. Because all tail calls originate from actor instances, the first argument to `actor.tailCall` is always `this`.

A chain of tail calls returns the return value of the last call in the chain. In this example, a caller making a blocking `actor.call` to `incr` remains blocked when `incr` returns a tail call expression. This expression is recognized by the KAR runtime, which atomically records the completion of `incr` and the request to invoke `set`. The caller of `incr` is eventually unblocked when it receives the `OK` value returned upon completion of the `set` method.

Thanks to the tail call, a failure may either interrupt `incr` or `set` but not both. If `incr` is interrupted, the `get` operation may be repeated. Because `set` has not run yet, the read value will remain the same. If on the other hand, `set` is interrupted, it may be repeated, but because the value to store has been captured as an invocation parameter to `set`, the same value will be written every time. In all cases, the value will be incremented exactly once.

A tail call to the same actor retains the actor lock, whereas a tail call to a different actor releases the lock. In this example, the lock is retained between the execution of `incr` and the matching execution of `set`. As a result, the sequences of `get` and `set` tasks resulting from distinct `incr` invocations cannot be interleaved (including retries). This guarantees holds even upon failure as KAR reliably persists the lock. In short, concurrent invocations of `incr` are serialized.
By extension the order of execution of the `get` and `set` tasks ensures that the corresponding `store.get` and `store.set` invocations are issued in order. However, a `store.set` invocation issued by `set` just before failing, could linger possibly delayed by the network or the data store itself, execute well out of order, and eventually incorrectly overwrite the result of a subsequent increment. For this reason, KAR ascertains that all pending invocations to external services such as `store.set` have been settled before retrying failed KAR tasks such as `set`.

While it may be tempting to read and write from a single method body or tempting to replace the tail call with a nested call, neither works. Consider these two incorrect variants:

```javascript
async incr() { await store.set('key', await store.get('key')+1); return 'OK' }
async incr() { return await actor.call(this, 'set', await store.get('key')+1) }
```

The top method may fail after `store.set` but before return, resulting in multiple increments upon retry. The bottom method, which uses a nested call rather than a tail call, may fail after the `set` call before returning, also leading to multiple increments upon retry. Unsurprisingly, there is no reliable way to implement a fault-tolerant increment without an atomic operation such as `actor.tailCall`.

### 2.4 Benefits

KAR augments a traditional actor-based programming model in two fundamental ways:

- KAR keeps track of call stacks, so it can 1) enable reentrant calls and 2) orchestrate, i.e., delay, the retry of a caller until after the callee’s fate has been decided: either completed without failure, preempted, known to have failed, or successfully retried.
- KAR introduces tail calls. A tail call atomically completes a call while issuing a next call. In addition, a tail call retains the lock on the caller if the caller is also the callee.

Tail calls greatly simplify reasoning about failures when applicable, while retry orchestration makes reasoning about failures tractable when tail calls are not applicable by ensuring past call stacks cannot overlap with retries of these call stacks.

Tail calls have two important, somewhat distinct use cases:

- Tail calls permit breaking complex methods into series of simple steps, simple methods chained via tail calls, enabling a divide-and-conquer approach to fault tolerance. Regular calls may also be used to break complex code. However, regular calls complicate reasoning about failures, as callers and callees may or may not fall victim of the same failure. Regular calls also complicate concurrency control even in the absence of failure, which is avoided by tail calls thanks to their locking behavior (irrespective of failures).
- Tail calls enforce a state-machine-like transition discipline not just within one actor but across actors. An actor may tail call other actors. With KAR, actors and state machines are orthogonal concepts. Actors may represent orders, payments, and shipments. Chains of tail calls can implement business processes like receiving an order and processing a payment.

Tail calls encode a key transactional pattern without bearing the cost of more general transactional mechanisms, both in terms of performance and productivity. A tail call is a single message that semantically is both a request and a response, rather than a collection of messages that must be emitted at once. There is no concept of aborted transaction or rollback for the developer to understand. Critically, tail calls enable developers to express these patterns in KAR even when the underlying cloud services or APIs being composed lack transactional support or retry capabilities as illustrated with the `incr` method code.
3 FORMAL SEMANTICS

We first formalize method invocations (3.1). We specify the syntax of terms that encode the possible points in the execution of a method and several forms of transitions that encode possible execution steps. We then specify the semantics of KAR by mapping method invocations to logical processes and using messages to transport invocation requests and responses among them (3.2). We define failures (3.3). We specify the runnable predicate that decides when pending invocation requests may be (re-)executed (3.4). We formalize KAR’s guarantees (3.5), cancellation, and preemption (3.6).

3.1 Base Language Specification

We assume a fixed but arbitrary program and abstract most of its syntax and semantics. We use the following alphabet:

- actor reference: $a$
- method name: $m$
- value: $v$
- actor state: $p$
- request id: $i$
- sequel: $s$

A point in the execution of a method is a pair $T/p$ where $T$ denotes the code that remains to be executed and $p$ denotes the state of the actor the method is running on.

$$T ::= m(v) \mid v \mid s \mid a.m(v) \triangleright s \mid v \triangleright s \mid a.m(v) \triangleright i \triangleright s \mid a.m(v) \quad \text{(term)}$$

The term $m(v)$ denotes the beginning of a method invocation including the method name $m$ and parameter $v$. The term $v$ denotes the return value. The term $s$ denotes an intermediate point in the method execution, more precisely the code remaining to be executed combined with the local state (local variables), in short the “sequel”. The term $a.m(v) \triangleright s$ denotes a nested method invocation (actor.call) where $a.m(v)$ denotes the callee and $s$ denotes the remainder of the caller to execute once the nested invocation has completed. The term $v \triangleright s$ denotes the reception of a result $v$ from a nested invocation with $s$ denoting the remainder of the caller. The term $a.m(v) \triangleright i \triangleright s$ denotes an asynchronous method invocation (actor.tell), where $s$ denotes the remainder of the caller that may execute concurrently with the callee. The term $a.m(v)$ denotes a tail call.

We assume the program is specified as a set of valid transitions with forms:

- $m(v)/p \rightarrow s/p$ \hspace{1cm} (begin)
- $s/p \rightarrow v/p$ \hspace{1cm} (end)
- $s/p \rightarrow s'/p$ \hspace{1cm} (step)
- $v \triangleright s/p \rightarrow s'/p$ \hspace{1cm} (return)
- $s/p \rightarrow a.m(v) \triangleright s'/p$ \hspace{1cm} (call)
- $s/p \rightarrow a.m(v) \triangleright i \triangleright s'/p$ \hspace{1cm} (tell)
- $s/p \rightarrow a.m(v)/p$ \hspace{1cm} (tail-call)

The execution of a method starts with a (begin) transition. Because our focus is on retry and ordering guarantees, we can abstract all the typical constructs of an imperative programming language such as sequences, conditionals, loops, or local variables in a single (step) form. The remaining forms permit method invocations (call, tell, tail-call), return a value (end), and receive the result of a nested invocation (return).

For example a getset method of a Latch actor that updates the actor state returning the previous value, may be specified as the following infinite set of transitions (for all $v$, for all $p$) assuming values and actor states have the same domain:

- $\text{getset}(v)/p \rightarrow \text{in}_v/p$
- $\text{in}_v/p \rightarrow \text{out}_p/v$
- $\text{out}_p/v \rightarrow p/v$

The families of sequels in$_v$ and out$_p$ represent intermediate points in the execution of the method capturing both its progress (before or after the value swap) and the local state of the method (the input or output value).

This set of transitions is not an execution semantics. It does not specify how to map actor references to actor states or how to chain execution steps. This is simply an abstraction of a source.
code designed to be language-neutral and focused on the features—actors and method invocations—that matter to KAR’s semantics. Similarly we do not specify how actor instances may be derived, e.g., from classes. Concretely, this set of transitions may be generated from a higher-level specification including control-flow constructs, a data model, and a mechanism to map actor references to sets of methods, for example by breaking actor references into a tuple (class type, instance id).

3.2 Message-Passing Semantics

Each method invocation runs in its own logical process. Processes communicate by means of invocation request and response messages. Processes running method invocations on the same actor reference share the actor state, i.e., the ability to read and write this shared state.

First we introduce some terms. A request id $i$ is an identifier. A return address $r$ is an optional request id.

\[
M ::= i \mapsto r \cdot a.m(v) \mid i \mapsto r \cdot v \quad \text{(message)}
\]

\[
F ::= (M, M', ...) \quad \text{(flow)}
\]

\[
P ::= s \mid i \Downarrow s \quad \text{(process)}
\]

\[
E ::= \{ i \mapsto a \cdot P, ... \} \quad \text{(ensemble)}
\]

\[
S ::= \{ a \mapsto p, ... \} \quad \text{(persistent state)}
\]

\[
R ::= F, E, S \quad \text{(runtime state)}
\]

A message $M$ is a 3-tuple consisting of a request id $i$, a return address $r$, and either a method invocation $a.m(v)$ or a return value $v$. The return address is the request id for the caller for a nested invocation, blank for an asynchronous invocation.

A flow $F$ is a possibly empty, ordered list of messages. List concatenation is written $F + F'$. To keep the syntax of our semantics simple, we formalize communications between actors as a unique flow, i.e., messages are totally ordered. The order of messages however is only tested in rule (leftmost) in Section 3.4, which identifies the oldest invocation request for a given actor reference $a$. Consequently, the position of a response message is irrelevant, as is the relative position of request messages sent to distinct actors.

A persistent state $S$ is a map from actor references $a$ to the states $p$ of these actors. We assume there is a default empty actor state, meaning for instance that the empty map $\emptyset$ maps every actor reference to the empty actor state.

A process $P$ is either a sequel $s$ or a guarded sequel $i \Downarrow s$. A guarded sequel denotes a process waiting for the result of a nested invocation with id $i$.

An ensemble $E$ is a map from request ids $i$ to processes $P$ tagged with actor references $a$. The tag denotes the actor this process is running on. The union of maps with disjoint key sets is written $E \cup E'$.

A runtime state $R$ is a 3-tuple consisting of a flow $F$, an ensemble $E$, and a persistent state $S$. We specify KAR’s semantics as a transition system of the form $F, E, S \Rightarrow F', E', S'$. The initial runtime state is made of a single request message with the main invocation and no return address: $\{ i \mapsto a.m(v) \}, \emptyset, \emptyset$. The rules of this semantics shown in Figure 3 are derived from the semantic forms of the base program specification.

Rule (begin) starts the execution of a pending request if it is runnable and not running already (because of the disjoint union of ensembles). The runnable predicate defined in 3.4 encapsulates complex logic including concurrency control and ordering constraints. Importantly for fault tolerance, the request message remains in the flow at this time.

Rule (step) ensures that a running actor may only update its own state. No actor can access the state of other actors.

Rule (end) atomically (1) discards the process at the end of the invocation, (2) discards the request message, and (3) enqueues the response message with the return value.
We specify failures by means of a single rule where $(\text{failure})$ denotes the ensemble $E$ with all entries labelled with $a \in A$ removed:

$$F, E, S \Rightarrow F, E \backslash A, S$$

Failures have no preconditions. They can happen at any time. A failure results in the loss of all the method invocations running on a set of actors. Messages and persistent state are not impacted. This rule reflects the nature of the cloud platform KAR is targeting. Individual OS processes, containers,
pods, or nodes can fail. On the other hand, messages queues and data stores are sophisticated systems orchestrating multiple distributed processes to provide a level of redundancy. These systems can transparently tolerate and mitigate failures up to a point, i.e., up to catastrophic failures. The catastrophic failure threshold depends on the particulars of given system implementation and configuration. The KAR runtime is meant to provide fault-tolerance guarantees in the absence of a catastrophic failure of the message queue or data store.

While we do not model transient actor state, our semantics can be easily extended to do so by dividing actor states into two components, one of which is lost in the (failure) rule.

This fail-stop failure model does not fully capture the complexities of a distributed runtime system where failures may be partial or transient and failure detection is imperfect. We explain in Section 4 how we address these issues by masking short transient failures and forcefully disconnecting application components deemed to have failed.

### 3.4 Runnable Invocations

The semantic rules above specify how to execute method invocations but not which invocations to run. This is the purpose of the `Runnable` predicate. In a non-reentrant, non-resilient, in-order actor system, an invocation is runnable if and only if it is the oldest invocation enqueued on this actor.

To handle reentrancy, we first introduce the `reachable` predicate defined by induction. The invocation id of the oldest, i.e., leftmost, invocation of actor `a` is reachable from `a` as well as any invocation of any actor `a'` transitively nested in this invocation, and there is no nested invocation with return address `i` queued in the flow:

\[
\begin{align*}
\text{reachable}(i, a, F) & \quad i \rightarrow a.m(v) \in F \\
\text{reachable}(i', a, F') & \quad i' \rightarrow a'.m(v') \notin F' \\
\text{reachable}(i, a') & \quad i' \rightarrow a'.m(v') \notin F' \\
\end{align*}
\]

An invocation with id `i` of actor `a` is runnable if it is reachable from `a`, i.e., if it is the oldest invocation of `a` or nested in this invocation, and there is no nested invocation with return address `i` queued in the flow:

\[
\begin{align*}
\text{reachable}(i, a, F) & \quad i \rightarrow a.m(v) \in F \\
\text{reachable}(i', a, F') & \quad i' \rightarrow a'.m(v') \notin F' \\
\text{reachable}(i, a') & \quad i' \rightarrow a'.m(v') \notin F' \\
\text{runnable}(i, F) & \\
\end{align*}
\]

In a failure-free execution, the latter condition is redundant. The only way for a nested invocation to exist is for the caller to be running already, waiting for the result from the callee. Because of failures however, the process for the caller may be lost before the process for the callee completes. We say the caller has to wait for the callee, in the sense that any retry of the caller `i` has to wait for every callee `i'` from any prior execution of the caller to finish first. This condition embodies the happen-before edges illustrated in Section 2.

### 3.5 Formal Guarantees

Let `⇒` be the transitive, reflexive closure of `⇒`. KAR’s main retry guarantee may be formalized as:

**Theorem 3.1.** If \{`i → a.m(v)`\}, \{0, 0\} ⇒ `F`, `E`, `S` ⇒ `F'`, `E'`, `S'` and `E` contains a process with id `i'` and tag `a'` and `F'` contains a request with id `i'` then `reachable(i, a', F')`.

Once a request starts running it remains reachable until it returns a result. Importantly, there is no guarantee the request will ever be runnable again because one attempt at running this request may make a nested call that never returns, which would delay a retry indefinitely. This is arguably the desired behavior as, in the absence of a failure, the invocation would have also been stuck.
Assuming the nested call eventually completes, the request becomes runnable again, i.e., retry-able. In short, the happen-before guarantee has priority over the retry guarantee.

The no retry after success guarantee (3.2), no concurrent retries of a call or two calls in a chain of tail calls guarantee (3.3), and happen-before guarantee (3.4) are safety properties:

**Theorem 3.2.** If $\{i \mapsto a.m(v)\}, \emptyset, \emptyset \Rightarrow F, E, S \Rightarrow F', E', S'$ and $F$ contains a response message with id $i'$ then $E'$ does not contain a process with id $i'$.

**Theorem 3.3.** If $\{i \mapsto a.m(v)\}, \emptyset, \emptyset \Rightarrow F, E, S$ then $E$ contains at most one process with id $i'$.

**Theorem 3.4.** If $\{i \mapsto a.m(v)\}, \emptyset, \emptyset \Rightarrow F, E, S$ and $F$ contains a request message with id $i'$ and return address $i''$ then runnable$(i'', F)$ is false.

**Proof.** 3.3 and 3.4 respectively follow from the definition of the ensemble of processes and the runnable predicate. 3.1 and 3.2 are established by induction over the structure of the semantics. The key observations are (1) that the reachable predicate only depends on the prefix of the flow up to the request under consideration so requests added to the tail of flow do not affect earlier requests and (2) that execution in a call stack completes from the inside out so there is no way for a request to disappear from the middle of a call stack. \(\square\)

### 3.6 Optional Cancellation and Preemption

As discussed in Section 2, if desired, KAR may automatically attempt to cancel pending nested invocations or preempt running nested invocations to avoid unnecessary computations, i.e., the computation of a result that is not needed anymore. Consequently, cancellation and preemption are only applicable to nested invocation (actor.call).

Because in a distributed system failure detection is not instantaneous, we formalize cancellation and preemption as racing with normal execution. The preemption of a process may happen at any point in its execution or not at all, once the conditions for preemption have been fulfilled.

Formally, we add one of the two rules of Figure 4 to the rules of Figure 3. Rule (cancel) removes a runnable nested invocation request from the flow if there is no process waiting for its result and this invocation is not already running. Rule (preempt) generalizes (cancel) using an auxiliary predicate:

\[
\text{runnable}(i, F \uplus (i \mapsto a.m(v)) \uplus F') \quad i' \xrightarrow{a} i \triangleright s \notin E \quad i \xrightarrow{a} T \notin E
\]

\[
\text{preemptable}(i, F \uplus (i \mapsto a.m(v)) \uplus F', E)
\]

An invocation is preetable if its caller has failed (as with cancellation) or if it is nested in an invocation whose caller has failed (unlike cancellation). If a calls b calls c and a fails, we want...
to preempt \textbf{b} and \textbf{c}. Cancellation on the other hand is designed not to interfere with running invocations. In this scenario, we cannot cancel \textbf{c} even if it has not started yet because its result is needed to run \textbf{b} to completion.

Rule (preempt) removes a runnable, preemptable invocation from the flow even if this invocation is already running, if so removing the matching process from the ensemble.

Both, cancellation and preemption proceed from the top of the call stack down thanks to the runnable precondition. If \textbf{a} calls \textbf{b} calls \textbf{c} and \textbf{a} fails, then \textbf{b} cannot be preempted before \textbf{c} is. This order ensures that the chain of happen-before relationships in a call stack is never broken: \textbf{a} waits for \textbf{b}, \textbf{b} waits for \textbf{c}, hence \textbf{a} waits for \textbf{c}.

4 IMPLEMENTATION

The message exchanges in the formal semantics closely match the actual implementation. However the semantics ignores important practical issues such as how to group actors into operating system processes, how to divide the flow of messages into separate queues, how to produce and consume messages out of order, and how to detect failures. We first consider these questions then explain the reconciliation algorithm that implements fault recovery.

4.1 Processes and Queues

Because KAR applications can combine heterogeneous components implemented using diverse programming languages and middleware frameworks, we built KAR as an out-of-process runtime. Application processes can either access the runtime’s functionality over HTTP/2 via its language-neutral REST API or via SDKs provided for Java, JavaScript, and Python. The entire KAR implementation is open source [KAR 2022].

A running KAR application consists of a dynamically varying number of components. Each component consists of a paired application and runtime process. Each process pair runs on the same logical node (same physical host, virtual machine, or Kubernetes pod). The (ab)normal termination of one process triggers the termination of the paired process. Application processes may be dedicated to specific tasks and replicated for horizontal scaling. Application processes announce which actor type(s) they support and KAR automatically places each instantiated actor in a compatible process. The runtime processes coordinate actor placement using a compare-and-swap operation on a persistent distributed data store. To reduce the frequency of store accesses, each runtime process maintains a placement cache that is invalidated on component failures.

KAR’s implementation allocates a dedicated message queue for each application component. Request messages are added to the callee’s queue. Responses are added to the caller’s queue for \texttt{actor.call} or to the callee’s queue for \texttt{actor.tell}. A \texttt{tell} waits for the queue to acknowledge the message to guarantee durability. A \texttt{call} blocks until a matching response message is received. In each component, a consumer thread listens for incoming messages. It delivers responses to suspended callers and dispatches requests to in-memory per-actor queues, except for reentrant invocations that bypass the in-memory queues.

KAR’s formal semantics makes a convenient but unrealistic assumption that it is possible to discard or alter messages in the middle of a queue. Typical production systems do not support this. Therefore, the implementation (1) only appends a message at the end of a queue and (2) expires messages in bulk. Thus, KAR (a) does not dequeue a request message immediately upon completion and (b) enqueues all tail calls at the end of the callee’s queue. To ensure a tail call to self runs next, KAR does not release the actor lock and recognizes the tail call as owning the lock (bypassing the in-memory queue just like a reentrant call). KAR expires the oldest messages after a configurable delay or above a configurable queue size. These parameters can be adjusted on a per-application basis to ensure messages are not expired before use. By default, messages expire after ten minutes.
We choose Redis [Redis 2022] to coordinate actor placement and implement KAR’s persistence API (actor.state). The runtime processes communicate with one another using Apache Kafka [Kafka 2022]. Kafka provides not only the reliable message queues, but also the authentication and discovery mechanisms, the consensus protocol, as well as the health monitoring and failure detection. Runtime processes authenticate with Kafka and form a Kafka consumer group for a Kafka topic that is unique to the application. This topic is dynamically partitioned into independent queues attached to each runtime process. Kafka detects the removal of a runtime process using heartbeats. When membership in the consumer group changes, Kafka allows the list of members to stabilize and then triggers a recovery, i.e., reconciliation.

Once Kafka removes a runtime process for the consumer group, this process no longer receives messages from Kafka but it is also prevented from sending more messages to Kafka, even if the process is not completely dead. Once the consumer group stabilizes, remaining healthy runtime processes also forcefully disconnect non-healthy processes from Redis before resuming the execution. In essence, this algorithm implements the fail-stop failures semantics of 3.3. Even if the Kafka failure determination is an approximation, we can guarantee that an application process deemed to have failed cannot further access or mutate actor state, hence there can be no overlap between state updates from an actor deemed failed and a replacement actor. As discussed in Sections 1 and 2, a mechanism for ascertaining that pending invocations have been settled should be implemented for every stateful service in use by KAR application components.

When an application component fails, KAR must decide what to do with the messages in its queue. All components temporarily stop sending and receiving messages. They reach a consensus on the list of live components and elect a reconciliation leader. This leader catalogs unexpired messages. Requests with a matching response or tail call are discarded. The remaining requests to failed components have to be preserved since they have not yet run to completion. KAR invalidates the placement decisions for all actors that were placed in a failed component and eagerly chooses a replacement component for those with pending requests. These pending requests are then appended to the queues of the selected components. KAR takes this opportunity to reorder requests messages according to the formal semantics (by moving tail calls to self earlier). It may be impossible to replace an actor if no component supports the actor type. KAR queues requests to unavailable types separately, revisiting this queue when new components are added to the application.

Request messages for nested calls (actor.call) include the request id for the caller. Reconciliation identifies every request with a pending nested call by transposing the callee-caller map. It alters the copy of the request message to include the id of the pending callee. When the request is received, the presence of this optional callee id instructs the runtime to postpone the retry of the request until a response from the callee is received, hence fulfilling happen before.

In the end, queues attached to failed components can be discarded or flushed for later reuse. A failure during reconciliation simply restarts reconciliation. Request messages already copied into the queues of live components are skipped.

To avoid magnifying transient failures, Kafka recommends and defaults to a 10 second grace period before deciding a process has failed. Given this time scale, there is room for a relatively long reconciliation phase. Section 6 reports that in our experiments, slightly less than half of the total detection and recovery time was spent on reconciliation.

Reconciliation time increases with the number of recent messages hence application components. So for larger scale systems, a different implementation may be necessary. An alternative to
reconciliation could use Kafka transactions [Apache 2016] to atomically (1) send the caller the call result via the caller’s queue and (2) log its completion in the callee’s queue, making it possible to match requests and completions within each failed component queue without global coordination. We leave this for future work.

4.4 Extensions

Cancellation. The formal semantics permit callees to be optionally preempted or canceled when the callers fail. Pragmatically, we chose to not implement preemption because the targeted language runtimes do not robustly support external preemption of individual running tasks. However cancellation was easy to implement efficiently. Just before invoking the language runtime to execute the callee, its runtime process checks the list of live application components established during the most recent reconciliation. If the caller’s component is not listed, execution is elided and a synthetic response message sent.

Deadlock detection. KAR implements dynamic deadlock detection by means of timeouts. By default, failing to acquire the lock on an actor instance times out after 2 minutes, throwing an exception that can be handled by the caller. The delay is configurable. In addition, we implemented a trace analyzer that identifies invocation cycles in execution traces (in real time or post mortem).

Fork-join parallelism. KAR’s synchronous call construct could be extended to support multiple concurrently-executing callees. This would required a minimal change to reconciliation, which should delay the retry of a caller until responses for all pending callees have been received.

5 CONTAINER SHIPPING APPLICATION

To demonstrate that KAR could be applied to a typical enterprise scenario, we teamed with a team of client-facing cloud developers to build out a realistic sample application. [KAR APPS 2022] An iterative development process continued for more than a year in which insights gained from the application work drove enhancements in both the KAR programming model and the KAR runtime system. These enhancements in turn enabled the application developers to simultaneously reduce the complexity of their code and to improve the fault tolerance capabilities of the application.

The starting point of the application work was a pre-existing Container Shipping application. The application models a subset of the business processes of a maritime shipping company. Clients can place orders to arrange shipping on a specific ship voyage of temperature sensitive products which require one or more refrigerated containers. Voyages are assigned to a shipping schedule between ports. Ships depart and arrive as scheduled and periodically broadcast their positions while in transit. At any time a container can suffer an anomaly indicating a failure of refrigeration. The detection of non-functional containers triggers different business logic depending on their state: in-transit, assigned to an order before departure, or empty.

This application was originally built without KAR. The development team designed it both to capture a specific customer scenario and to serve as a reference application for event-driven architectures. Interestingly, the original design [Shipping 2018a] was described in terms of actors and their interactions, but the actual implementation was a collection of classic microservices connected via a Kafka-based event bus [Shipping 2018b]. In the process of deriving an efficient implementation, the natural actor-based domain model was abandoned. As a demonstration of KAR’s capabilities, we re-implemented the core business logic following the original actor-based design in approximately 5,000 lines of Java code using the OpenLiberty-based KAR Java SDK.

The high level software components of the KAR-based application are shown in Figure 5a. The BrowserUI is implemented with Angular and is used to visualize application behavior and provide an easy interface for controlling the simulators that drive it. The WebAPI is a stateless service
that provides the application interface. It receives updates from stateful actor components and pushes that information in real time to BrowserUI. The Order actor implements order logic and maintains persistent state for a single order. An order actor instance is instantiated on an order creation request and its state is removed upon arrival at its destination port. The Voyage actor implements voyage logic and maintains the persistent state for a single voyage. A voyage actor instance is instantiated on its first order or on departure if empty. Its state is removed upon arrival. The Depot actor implements container management logic and manages the container inventory for a port. Container data includes references to its owning order and voyage. The AnomalyRouter is a singleton actor that maintains a mapping of container locations that enables it to route container anomaly events to the appropriate depot or voyage actor. There are also singleton OrderManager, VoyageManager, and DepotManager actors that manage global state and track statistics.

Figure 5b illustrates the intended production deployment of the application with replicated instances of each component to support failover and scale out. The Order, Voyage, and Depot actor types are configured to be hosted on the “Actors Server” while the other actor types are hosted on the “Singletons Server”; this enables these two actor-hosting components to be scaled independently.

Container shipping application components are driven by events including: order creation requests, voyage position changes, and container anomalies. Custom event simulators were developed to automatically generate load to stress both the application and KAR. The simulators maintain no application state. They interface with the WebAPI and relevant actors. Simulator parameters such as the order generation and anomaly rate are controlled through BrowserUI.

After completing the first version of the application and associated load-testing scaffolding, development focus shifted to scalability and fault testing. Throughout this process, the developers found that KAR’s actor programming model enabled them to refactor the application code almost as easily as if it were a monolithic procedural program. It is well known that the potential for data races makes it hard to write correct concurrent and distributed code. The actor programming model eliminates races within each actor instances. However, high-level data races are still possible in-between actors. In particular, we realized that faults and the subsequent under-orchestrated retries of failed tasks exacerbated the potential for high-level data races. Specifically, we observed developers struggling with overlapping retries of 1) consecutive steps in a logical sequence and 2) subtasks of failed tasks. As shown by a representative example in Figure 6a, the developers had to add logic to deal with method retries in the prologues of many actor methods. The process of doing so was labor-intensive and error-prone. It also resulted in non-local reasoning: for example, a failure during createOrder after Actor.tell sends its message but before State.set completes
public void createOrder(JsonObject message) {
    // Detect duplicate executions
    if (order != null && OrderStatus.BOOKED.name().equals(order.getStatus())) {
        // Workflow has already completed. Report result to external client
        JsonObjectBuilder bookingStatus = Json.createObjectBuilder()
            .add(ReeferConfig.STATUS_KEY, Constants.OK)
            .add(ReeferConfig.ORDER_ID_KEY, String.valueOf(this.getId()));
        Kar.Services.post(ReeferConfig.REFERSERVICE, "/orders/booking/success", bookingStatus.build());
    }
    if (order != null && OrderStatus.PENDING.name().equals(order.getStatus())) {
        // Workflow in progress but this step already completed.
        return;
    }
    this.order = new Order(message);
    // Initiate next workflow step
    ActorRef voyage = Kar.Actors.ref(ReeferAppConfig.VoyageActorType, order.getVoyageId());
    Kar.Actors.tell(voyage, "reserve", order.getAsJsonObject());
    // Record progress by persisting pending order
    order.setStatus(OrderStatus.PENDING);
    Kar.Actors.State.set(this, Constants.ORDER_KEY, order.getAsJsonObject());
}

(a) Code snippet from Container Shipping built using KAR v1.2 (weaker retry orchestration semantics).

public Kar.Actors.TailCall createOrder(JsonObject message) {
    this.order = new Order(message);
    order.setStatus(OrderStatus.PENDING);
    Kar.Actors.State.set(this, Constants.ORDER_KEY, order.getAsJsonObject());
    ActorRef voyage = Kar.Actors.ref(ReeferAppConfig.VoyageActorType, order.getVoyageId());
    return new Kar.Actors.TailCall(voyage, "reserve", order.getAsJsonObject());
}

(b) Code snippet from Container Shipping built using KAR v1.3 (happen-before and tail calls).

Fig. 6. Two versions of the first step of the order creation workflow of the OrderActor. In the version with tail calls, duplicate execution checks can be safely eliminated.

would result in its retried execution issuing a duplicate invocation of reserve that would need to be detected and handled in the VoyageActor’s logic. These observations led us to develop the current KAR semantics which were designed to eliminate these classes of data races by construction with 1) tail calls and 2) happen-before. The simplified and fully correct code enabled by these semantics is shown in Figure 6b.

Figure 7 depicts the steps taken during a successful execution of the workflow for accepting and processing a client order. This workflow illustrates how pervasively the implementation of the application’s business depends on the capabilities provided by the KAR programming model. The execution spans 16 methods of 5 actor types, and is primarily orchestrated by tail calls. However it also includes the use of a synchronous reentrant call by the Order actor to create a sub-orchestration that ends by notifying the WebAPI that the order has been accepted and an asynchronous tell that spawns a background update of the ScheduleManager. Four of the methods, indicated by shaded boxes, update externally managed state; tail calls isolate these updates to simplify the programmer’s reasoning about retrying them on failures. Throughout the workflow, failure recovery is simplified by the purely local reasoning enabled by KAR’s retry orchestration.

6 EVALUATION

Our empirical evaluation is designed to provide evidence to support two hypotheses. First, KAR-based applications can automatically and reliably detect and recover from failures. Second, KAR’s actor-based programming model and external runtime system are not significantly less performant than the reliable messaging system on which they are built.
6.1 Failure Detection and Recovery

In KAR’s target environment of the cloud, failures are relatively infrequent, but may be clustered. As a result of a failure, one or more application components may exit abruptly and without notification. We designed our fault-testing scenarios accordingly, with the time-saving modification of “fast forwarding” through the failure-free intervals by randomly injecting the next fault less than two minutes after the application fully recovers from the previous one.

We use the Container Shipping application described in the previous section as the user workload for our fault-injection experiments. To perform the experiments in a completely controlled fashion, we use k3d [K3D 2021] to create a virtual five node Kubernetes cluster. Using node affinities, we deploy all Kubernetes system pods, Kafka, Redis, and the simulators on three nodes of this cluster. We deploy two replicas of each remaining application component on the other two “victim” nodes. Using an automated test harness, we cause a series of abrupt failures by instructing k3d to do a hard stop on a randomly selected victim node. Each failure results in the abrupt termination of multiple application and runtime processes. After normal application operation has automatically recovered on replica processes, the node is restarted which spawns new replicas.

Since the node running the simulators is never killed, we can easily verify that failures never cause submitted orders to be lost. The application also dynamically checks additional application-level invariants, such as that ships arrive and depart as scheduled carrying their expected cargoes, that ships and containers neither disappear or appear out of thin air, and that simulation time continuously advances. None of these invariants were ever violated during the experiments.

During a 48 hour run of the application, we injected 1,000 single node failures. The typical outage caused by a failure lasted for 22 seconds, with a minimum elapsed time of 16.1 seconds and a maximum of 31.2 seconds. The typical failure took 9 seconds to detect followed by an additional 13 seconds to recover before normal execution resumed. Figure 8a breaks each such outage into
Fig. 8. Analysis of 1,000 single node failures during a 48 hour run of the Container Shipping application.

Table 1. Summary statistics for 1,000 failures (seconds)

|                        | Average | StdDev | Median | Min    | 95th% | 99th% | Max    |
|------------------------|---------|--------|--------|--------|-------|-------|--------|
| Total Outage           | 22.139  | 2.114  | 22.015 | 16.117 | 25.047 | 29.025 | 31.207 |
| Detection              | 9.053   | 0.907  | 9.084  | 7.217  | 10.493 | 10.738 | 11.022 |
| Consensus              | 2.437   | 0.086  | 2.443  | 2.232  | 2.497  | 2.525  | 3.197  |
| Reconciliation         | 10.649  | 1.967  | 9.098  | 6.019  | 12.075 | 18.036 | 21.035 |

its three main components: the time for Kafka to detect a failure, the time to reach a distributed consensus on the new application topology, and the time spent by KAR in reconciliation. Table 1 reports the detailed statistics. On average, reconciliation time is just under half of the total outage time. As indicated by the 95th% and 99th% data, reconciliation has a longer tail than the two other phases. Log analysis revealed that the outliers correlate with Kafka snapshotting and log rotation tasks. As reconciliation reads a large number of messages, it is particularly sensitive to background Kafka processing.

Figure 8b presents an application-level view of the outages by showing a scatter plot of the maximum order latency observed in each time window surrounding a failure. In failure-free operation, the average order latency is around 100 milliseconds. Around failures, this spikes to an average (median) of 24.5 (24.0) seconds, with a maximum of 43.8 seconds and a minimum of 7.2 seconds. The maximum order latency during a failure is occasionally less than the outage time because the application is replicated. During the handful of failures where all in-flight orders were being handled by unimpacted replicas, processing could continue normally until interrupted by the consensus and reconciliation phases.

We also tested two more challenging failure scenarios. First we verified that KAR can robustly handle failures during recovery by injecting 1,000 paired node failures where the second failure was timed to occur during the consensus or reconciliation phases of recovery. Second, we performed 500 iterations of a complete application failure scenario where all application and runtime processes except the simulator were killed abruptly and then restarted after waiting for 30 seconds. KAR and the application were able to handle all of these failures successfully.

### 6.2 Reliable Messaging

For these experiments, our testbed is a five node Kubernetes v1.22 cluster provisioned via the managed Kubernetes service of the IBM public cloud. Each (virtual) worker node is a b3c.4x16 configuration, which has 4 CPUs, 16 GB of memory, and runs Ubuntu 18.04. The nodes are connected via a 1Gbps virtual private network. We deploy KAR v1.3.1 on this cluster in conjunction with
three different Kafka and Redis configurations: \textit{ClusterDev}, \textit{ClusterProd}, and \textit{Managed}. The \textit{Cluster} configurations run deployments of Kafka and Redis within the Kubernetes cluster. With \textit{ClusterDev}, Kafka and Redis data is not backed by persistent storage and there is only one replica of each. With \textit{ClusterProd}, Kafka and Redis data is backed by attached Persistent Volumes that support 1000 IOPS; Kafka is configured with 3-way replication. With \textit{Managed}, Kafka and Redis are instantiated using IBM Cloud’s fully managed production services: Event Streams and Databases for Redis. These managed instances are provisioned in the same cloud region as the Kubernetes cluster.

Table 2 reports the end-to-end latency in milliseconds of a minimal request-response communication pattern with a small payload (20 bytes of user data) on these three different KAR system configurations. We report the median latency of 10,000 iterations. The two communicating processes are placed on different worker nodes. The first two columns are baseline measurements that do not involve the KAR runtime. The \textit{Direct HTTP} column reports the time required for a non-reliable request/response communication (a POST request over an HTTP connection) between two Node.js processes. The second column, \textit{Kafka Only} isolates the end-to-end latency for two Go processes that send messages by connecting directly to Kafka using the same Go-based client as the KAR runtime. The final two columns report the latency for KAR actor method invocations using the Node.js KAR SDK. \textit{Kar Actor} is the default configuration; \textit{KAR Actor (no cache)} disables the actor placement cache that short circuits Redis access on most actor method invocations.

|               | Direct HTTP | Kafka Only | KAR Actor | KAR Actor (no cache) |
|---------------|-------------|------------|-----------|----------------------|
| \textit{ClusterDev} | 2.60        | 4.35       | 6.62      | 7.12                 |
| \textit{ClusterProd} | 2.60        | 10.62      | 13.41     | 14.31                |
| \textit{Managed}     | 2.60        | 14.56      | 15.80     | 18.06                |

The first conclusion from these numbers is that, unsurprisingly, there is a measurable cost to communicating through reliable message queues vs. non-resilient direct HTTP connections. When Kafka is replicated for fault tolerance, the \textit{Kafka Only} request-response latency is 4X to 5.6X higher than in \textit{Direct HTTP}. These Kafka latencies are comparable with others reported in the literature, for example Mukherjee et al. [2019] reports an end-to-end message latency of 9 milliseconds using a replicated cloud-deployed Kafka configuration. Second, the extra inter-process communication introduced by the KAR external runtime design and the bookkeeping associated with actor method invocation only adds modest overhead to the base cost of using reliable messaging. In the configurations that we believe are representative of KAR’s intended production use cases, \textit{Managed} and \textit{ClusterProd}, \textit{KAR Actor} incurs 9% and 26% additional latency respectively when compared to \textit{Kafka Only}. Finally, we can see that although caching actor placement only provides a marginal benefit in \textit{ClusterDev} and \textit{ClusterProd}, it has more impact in \textit{Managed} where the Redis instance is not co-located in the same Kubernetes cluster as the application processes.

7 RELATED WORK

Our programming model and some aspects of its implementation were inspired by the \textit{Distributed Application Runtime} (DAPR) project [DAPR 2020a,b]. Both systems delegate dynamic service discovery and cross-component communication to a mesh of external runtime processes. The runtime exposes a language neutral REST API, but is augmented with SDKs for selected languages and middleware frameworks to simplify programming.
The virtual actor model that is used by both DAPR and KAR was one of the main innovations of the Orleans system [Bernstein et al. 2014; Bykov et al. 2011]. Virtual actors improve on the usability of previous actor systems such as Akka [Akka 2011] and Erlang [Armstrong 2010] by making actor placement and life-cycle management the responsibility of the runtime system instead of the application programmer.

The application-level fault tolerance capabilities enabled by KAR go beyond those provided by DAPR or Orleans. Both previous systems view individual actors as the unit of fault tolerance and recovery, and make weaker guarantees about the failure semantics of multi-actor interactions. DAPR and Orleans offer reliable, at-least-once message delivery, but do not guarantee that a successfully completed message will never be re-delivered as part of failure recovery. KAR is the only one of the three systems that fully explores the combination of call chain actor reentrancy and fault tolerance. Orleans 2.x did not correctly implement full call chain reentrancy [Orleans-5456 2019], and call chain reentrancy has been removed in later versions [Orleans-7397 2021]. DAPR v1.6 provides call chain reentrancy as a preview feature that is not supported by any of its SDKs and does not describe how enabling it will interact with failure recovery [DAPR Reentrancy 2022].

Reliable State Machines (RSM) is a framework for developing cloud-native applications with a strong emphasis on fault-tolerance. Mukherjee et al. [2019] defines the formal semantics of RSM and describes an implementation built on reliable messaging services provided by Microsoft Azure. Like RSM, KAR relies on reliable message queues to connect application components and build a replay-able log, but unlike RSM, KAR permits applications to persist state outside of this log. KAR extends on the RSM programming model by making state machines and actor instances orthogonal concepts. KAR state transitions use the same tail call mechanism within and across actors. Furthermore, KAR supports composing state machines with other programming patterns for achieving fault tolerance.

The Resilient X10 system [Crafa et al. 2014; Grove et al. 2019] emphasizes the importance of preserving the happens-before invariant for enabling fault-tolerant distributed programming. X10’s finish-async programming model supports a more general task graph structure than KAR’s simple caller-callee relationship. At the time of a failure, a KAR task can have at most one live child; X10 tasks may have many. As a result, X10 requires substantially more complicated fine-grained distributed bookkeeping to ensure that a task cannot finish, hence be retried, before any of its subtasks. Unlike KAR, Resilient X10 does not automatically retry failed tasks. KAR automates and orchestrates retries, thus eliminating much of the hand-written application-specific recovery code required by X10.

Many prior systems simply retry apparently failed tasks to achieve a measure of fault tolerance [Cutting and Baldeschwieler 2007; Dean and Ghemawat 2004; White 2009; Zaharia et al. 2012]. This works well with side-effect free tasks, but is challenging to apply effectively to complex workflows that can contain non-idempotent operations or interactions with external systems.

HPC applications have long relied on coordinated checkpoint/restart both as a mechanism for resiliency and to decompose long-running applications into more schedulable units of work [Elnozahy et al. 2002; Sato et al. 2012]. Checkpoint/restart has also been explored for fault tolerance in distributed actor systems. Field and Varela [2005] develop a formal semantics of transactors and show that it is possible to obtain globally consistent checkpoints in a loosely coupled system by exploiting the structure of actor interactions. The AEON system [Sang et al. 2020] explores a practical implementation of this approach. AEON restricts actor interactions to occurring in directed acyclic graphs (DAGs) and exploits their dominator structure to drive checkpointing operations. In contrast, KAR’s support for fault-tolerant reentrancy avoids restricting actor interactions to DAGs and enables cyclic multi-actor interactions.
Transaction protocols like two phase commit provide fault tolerance over grouped operations for online transactional processing and ideally provide ACID guarantees [Gray and Lamport 2006]. Later transaction protocols target distributed architectures and minimize locking to achieve higher scalability and performance but with weaker guarantees. For example, SAGA [Garcia-Molina and Salem 1987] can abort a transaction using sequentially executed, compensatory actions to rollback independently committed operations to a clean state, while Thorp optimizes 2PL/2PC to support actor-based transactions in the Microsoft Orleans service [Eldeen and Bernstein 2016]. Beldi [Zhang et al. 2020] extends Olive [Setty et al. 2016] and utilizes transactions to provide exactly once semantics to “stateful serverless functions” – serverless functions that maintain state in external NoSQL databases. Beldi accomplishes this by providing a library that wraps select NoSQL stores; all access by the functions to the NoSQL store must go through Beldi’s API to realize the promised exactly once execution semantics.

Durable Functions extends Azure Functions [Microsoft 2016] with entities and orchestrations whose state/progress is automatically persisted and restored after a failure [Microsoft 2018]. Burckhardt et al. [2021] formalizes an idealized failure-free semantics for Durable Functions, and establishes that even in the presence of failures a compute-storage model preserves an observably exactly-once execution of the Durable Functions application. Key to this proof is the assumption that all observable application state (entity state, message queues, and orchestration progress) is persisted in a single durable store that is managed by the Durable Functions runtime and can be updated atomically. Enabled by this strong assumption about application state, Durable Functions provides a weaker retry semantics than KAR. Durable Functions allows multiple concurrent executions of the same work item (only one of which will be able to successfully commit its updates to the store on completion) ([Burckhardt et al. 2021] section 5.3). Unlike Durable Functions, KAR embraces an open world assumption. KAR applications are not restricted to using a single system managed store. KAR’s more precise retry orchestration facilitates interactions with external services that may have irrevocable side effects. KAR also provides a more flexible programming model by not imposing a strict stratification between activity functions, entity functions, and deterministic orchestrator functions. KAR actors combine mutable state and control-flow state (active tail call in a chain). Moreover, KAR actor methods need not be deterministic, making it easy for instance for a task to do something else after repeated retries.

8 CONCLUSIONS
An increasingly rich collection of applications are being built for and deployed on diverse cloud platforms. The cloud is no longer just a platform for stateless functions, batch analytics, or other fault-oblivious side-effect free computations. Enterprises are migrating mission-critical stateful applications that interact with multiple external stateful services to the cloud. KAR provides a programming model and supporting runtime that is designed to simplify and support the development of such applications, while taking advantage of existing cloud capabilities. In the presence of failures, KAR not only orchestrates retries of individual tasks but also worries about verticals and horizontals, i.e, call stacks and call chains. KAR demonstrates it is possible to productively develop fault-tolerant applications even if the application state is split among multiple, independent persistent services. In this paper, we formalized the core semantics of KAR to precisely formulate and establish its fault tolerance guarantees, outlined an implementation built on Kafka, and described a fault tolerant application built using KAR.

ARTIFACT AVAILABILITY
The source code of the KAR system and the Container Shipping application used in our experiments is available in a software artifact archived on Zenodo [Grove et al. 2023]. The code is based
on KAR version 1.3.3 and KAR-APPS 1.2, which are also available from the project’s GitHub repositories [KAR 2022; KAR APPS 2022]. In addition to this source code, the artifact also contains and documents the scripts, microbenchmarks, and analysis tools used for all experiments reported in Section 6.

REFERENCES

Akka 2011. Akka Actor Model. https://akka.io/docs/
Apache. 2016. KIP-98 - Exactly Once Delivery and Transactional Messaging. https://cwiki.apache.org/confluence/display/KAFKA/KIP-98+-+Exactly+Once+Delivery+and+Transactional+Messaging
Joe Armstrong. 2010. Erlang. Commun. ACM 53, 9 (Sept. 2010), 68–75. https://doi.org/10.1145/1810891.1810910
Phil Bernstein, Sergey Bykov, Alan Geller, Gabriel Kliot, and Jorgen Thelin. 2014. Orleans: Distributed Virtual Actors for Programmability and Scalability. Technical Report MSR-TR-2014-41. https://www.microsoft.com/en-us/research/publication/orleans-distributed-virtual-actors-for-programmability-and-scalability/
Sebastian Burckhardt, Chris Gillum, David Justo, Konstantinos Kallas, Connor McMahon, and Christopher S. Meiklejohn. 2021. Durable Functions: Semantics for Stateful Serverless. Proc. ACM Program. Lang. 5, OOPSLA, Article 133 (Oct. 2021), 27 pages. https://doi.org/10.1145/3485510
Sergey Bykov, Alan Geller, Gabriel Kliot, James R. Larus, Ravi Pandya, and Jorgen Thelin. 2011. Orleans: cloud computing for everyone. In Proc. 2nd ACM Symposium on Cloud Computing (Cascais, Portugal) (SOCC ’11). ACM, New York, NY, USA, Article 16, 14 pages. https://doi.org/10.1145/2038916.2038932
Silvia Crafa, David Cunningham, Vijay Saraswat, Avraham Shinnar, and Olivier Tardieu. 2014. Semantics of (Resilient) X10. In Proc. 28th European Conference on Object-Oriented Programming. 670–696. https://doi.org/10.1007/978-3-662-44202-9_27
Doug Cutting and Eric Baldeschwieler. 2007. Meet Hadoop. In O’Reilly Open Software Convention. Portland, OR.
DAPR 2020a. DAPR GitHub Organization. https://github.com/dapr
DAPR 2020b. DAPR Project Website. https://dapr.io
DAPR Reentrancy 2022. How-to: Enable and use actor reentrancy in Dapr. https://docs.dapr.io/developing-applications/building-blocks/actors/actor-reentrancy/
Jeffrey Dean and Sanjay Ghemawat. 2004. MapReduce: Simplified data processing on large clusters. In Proc. 6th Conference on Symposium on Operating Systems Design & Implementation (San Francisco, CA) (OSDI’04). 10–10.
Tamer Eldeeb and Phil Bernstein. 2016. Transactions for Distributed Actors in the Cloud. Technical Report MSR-TR-2016-1001. https://www.microsoft.com/en-us/research/publication/transactions-distributed-actors-cloud-2/
E. N. Elnozahy, Lorenzo Alvisi, Yi-Min Wang, and David B. Johnson. 2002. A survey of rollback-recovery protocols in message-passing systems. ACM Computing Survey 34, 3 (2002), 375–408.
John Field and Carlos A. Varela. 2005. Transactors: A Programming Model for Maintaining Globally Consistent Distributed State in Unreliable Environments. In Proceedings of the 32nd ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (Long Beach, California, USA) (POPL ’05). Association for Computing Machinery, New York, NY, USA, 195–208. https://doi.org/10.1145/1040305.1040322
Hector Garcia-Molina and Kenneth Salem. 1987. Sagas. In Proceedings of the 1987 ACM SIGMOD International Conference on Management of Data (San Francisco, California, USA) (SIGMOD ’87). Association for Computing Machinery, New York, NY, USA, 249–259. https://doi.org/10.1145/38713.38742
Jim Gray and Leslie Lamport. 2006. Consensus on Transaction Commit. ACM Trans. Database Syst. 31, 1 (March 2006), 133–160. https://doi.org/10.1145/1132863.1132867
David Grove, Sara S. Hamouda, Benjamin Herta, Arun Iyengar, Kiyokuni Kawachiya, Josh Milthorpe, Vijay Saraswat, Avraham Shinnar, Mikio Takeuchi, and Olivier Tardieu. 2019. Failure Recovery in Resilient X10. ACM Trans. Program. Lang. Syst. 41, 3, Article 15 (July 2019), 30 pages. https://doi.org/10.1145/3332372
David Grove, Olivier Tardieu, Jaroslav Cwiklik, Edward Epstein, Gheorghe-Teodor Bercea, and Paul Castro. 2023. Reliable Actors with Retry Orchestration. https://doi.org/10.5281/zenodo.7805564
K3D 2021. K3D Project Website. https://k3d.io/
Kafka 2022. Apache Kafka Project Website. https://kafka.apache.org
KAR 2022. KAR GitHub. https://github.com/ibm/kar
KAR APPS 2022. KAR Applications GitHub. https://github.com/ibm/kar-apps
Microsoft. 2016. Azure Functions. https://functions.azure.com/
Microsoft. 2018. Durable Functions Website. https://docs.microsoft.com/en-us/azure/azure-functions/durable/
Philipp Moritz, Robert Nishihara, Stephanie Wang, Alexey Tumanov, Richard Liaw, Eric Liang, Melih Elibol, Zongheng Yang, William Paul, Michael I. Jordan, and Ion Stoica. 2018. Ray: A Distributed Framework for Emerging AI Applications. In 15th USENIX Symposium on Operating Systems Design and Implementation (OSDI 18). USENIX Association, Carlsbad, CA, 561–577. https://www.usenix.org/conference/osdi18/presentation/moritz

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