Actor Database Systems: A Manifesto

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ABSTRACT
Interactive data-intensive applications are becoming ever more pervasive in domains such as finance, web applications, mobile computing, and Internet of Things. Typically, these applications are architected to utilize a data tier for persistence. At one extremity, the data tier is a simple key-value storage service, and the application code is concentrated in the middle tier. While this design provides for programmability at the middle tier, it forces applications to forego classic data management functionality, such as declarative querying and transactions. At the other extremity, the application code can be colocated in the data tier itself using stored procedures in a database system. While providing rich data management functionality natively, the resulting lack of modularity and state encapsulation creates software engineering challenges, such as difficulty in isolation of bugs and failures or complexity in managing source code dependencies. In addition, this monolithic architectural style makes it harder to scale the application with growing request volumes and data sizes. In this paper, we advocate a new database system paradigm bringing to developers the benefits of these two extremes, while avoiding their pitfalls. To provide modularity and reasoning on scalability, we argue that data tiers should leverage the actor abstraction; at the same time, these actor-based data tiers should offer database system features to reduce bugs and programming effort involved in state manipulation. Towards this aim, we present a vision for actor database systems. We analyze current trends justifying the emergence of this abstraction and discuss a set of features for these new systems. To illustrate the usefulness of the proposed feature set, we present a detailed case study inspired by a smart supermarket application with self-checkout.

1 INTRODUCTION
Online services are becoming increasingly ubiquitous requiring management of substantial data along with low-latency interactions. These interactive data-intensive applications include online games, social networks, financial systems, operational analytics data management, web applications and upcoming Internet-of-Things (IoT) and mobile computing platforms [20, 22, 31, 52, 57]. The standard methodology to architect these applications is to segregate the server-side application logic across an application (or middle) tier and a data tier. Opinions seem to be divided on how to architect the application code across the application and the data tiers. Existing approaches can be classified across two extreme ends: (1) Architect the data tier as a dumb storage abstraction with the entire logic in the application tier; (2) Architect the application tier to be completely stateless using the database as a full-fledged programming environment with the entire data manipulation logic in the data tier.

In approach (1), database functionality such as transactions and declarative querying are either sacrificed or underutilized. This approach leads to increased demand on the middle tier for well-defined state management functionality under concurrency and failures. This demand can be met either by: (a) building the necessary features in the application tier, however leading to reduced productivity [14, 49]; or (b) utilizing application frameworks with only limited transactional features in the middle tier, however leading to misconceptions and, consequently, incorrect applications [13].

In approach (2), the database is conceptualized as a monolithic entity where the state is maintained and manipulated through sequential programs written using declarative querying and limited general purpose programming constructs, e.g., stored procedures without modern object-based modularity features. The lack of modularity in this approach makes it hard to identify bugs, isolate failures and maintain application code, especially with growing data and application complexity. Furthermore, the monolithic design makes it hard for the application developer to reason about the scalability and performance of the data tier.

The actor programming model has desirable primitives for concurrency and modularity [2]. By encapsulating state, providing single-threaded semantics for encapsulated state manipulation, and encouraging an asynchronous function-shipping programming paradigm, actors provide a general, modular and concurrent computational model. However, actors expose state management responsibilities such as durability, global state consistency across actors, and failure management to the application developer. Despite these shortcomings, actor frameworks and languages, such as Akka [4], Erlang [9, 29] and especially the virtual actor model of Orleans [16], are increasingly being used to build soft caching layers designed to scale to millions of actors deployed across hundreds of servers using existing cloud-computing infrastructure. These applications vary in diversity, including as examples chat and call services, crowd collaboration and synchronization platforms, mobile and social payment platforms, real-time bidding applications, online games, and even IoT streaming from space balloons [5, 30, 39]. The popularity of these applications points to the appeal of the actor programming model, which allows application developers to design modular, scalable programs for deployment in an increasingly parallel and heterogenous cloud-computing infrastructure without sacrificing developer productivity.

In line with microservices [32], we believe the data tier should be programmed as a logically distributed runtime with the necessary configurable state management guarantees that are appropriate for the application. In addition, the programming abstraction of the data tier should allow for modular, scalable, performance-portable and cloud-ready design of application programs. Towards this goal, we call on the database community to define and explore the new abstractions of actor database systems, which provides the
illusion of a distributed logical runtime enriched with data management features. Actor database systems are envisioned to increase the programmability of the data tier, where the application hard state with strong guarantees of durability and consistency is maintained. As such, actor database systems are complementary to the design of the middle tier, where stateless application logic or alternatively soft-state resides. Even if the middle tier employs actors, as in Orleans [16], such a middle tier cannot subsume the data tier, since only weak state management guarantees are provided and consistency is traded off for availability.

Contributions and Roadmap. This paper proposes a new vision to marry actors and database systems. Specifically, the paper makes the following contributions:

(1) To motivate the actor database system paradigm, we discuss in Section 2 an example of an interactive data-intensive application in the domain of smart supermarkets. The example illustrates at a high level the varied features that a data tier implemented as an actor database system should support.

(2) We argue in Section 3 why the time is ripe for the emergence of the new abstraction of actor database systems by analyzing a number of current trends in the design of interactive data-intensive applications.

(3) Given the aforementioned analysis, we present in Section 4 a set of tenets and features that should be followed by every actor database system.

(4) To illustrate the potential interplay of these features with applications, we drill down in Section 5 on a case study of the smart supermarket application introduced as the running example. After discussing modularity, querying, and transactions through application pseudocode, we illustrate the promise of improved performance with asynchronicity in actor database systems by implementing and evaluating the application in an actor database system prototype.

In Section 6, we discuss related work before concluding.

2 MOTIVATING EXAMPLE

We motivate the integration of actors and database systems by an example that illustrates the needs of many emerging interactive data-intensive applications. Consider a simplified future IoT supermarket application for next-generation self-checkout [8, 43]. The application models the workflow of a customer carrying a smart shopping cart equipped with sensors that can detect physical items inside it. The smart cart periodically interacts with a backend service, which is itself implemented using an actor database system in the data tier. Figure 1 shows a set of database actors for this application, along with a chain of function invocations triggered by the functionality to add items and checkout.

The application is functionally decomposed into actors to represent customers, carts, store sections, and group managers for marketing campaigns. For modularity, state is encapsulated within each actor; however, for programmability and declarative specification, the state of each actor is abstracted by a set of relations and application functions employ declarative queries against relations. For example, the customer actor contains relations recording general information about the customers and their store visits, while the cart actor contains relations recording the contents of the cart. The store section actor contains relations recording the inventory of the store section and its purchase history, and the group manager contains relations recording the fixed discount available on each item specialized for a group of customers.

For database-style consistency in state manipulation, selected functions perform actions atomically, in particular the add_items and checkout functions. When the add_items function is invoked, we atomically update the cart with the latest prices and fixed discounts. Similarly, when checkout is called, we atomically compute demand-based variable discounts, update inventory, and compute aggregates for the order. In addition, these functions need isolation under concurrent updates, e.g., when multiple simultaneous checkouts update the same items in the inventory and calculate demand-based variable discounts. Furthermore, the changes made by checkout require durability for recording purchase history and updating the inventory.

Even though it may seem natural to treat functions such as add_items and checkout as classic database transactions, the interaction of database-style functionality with actors brings new challenges and opportunities. In particular, both transactions invoke a number of sub-transactions across various actors. In the actor model, function calls between actors are asynchronous. For example, add_items asynchronously invokes get_customer_info and get_price on customer and store section actors, while checkout invokes get_variable_discounts_update_inventory on store section actors. This asynchronicity in invocations exposes intransitiveness, which must interplay cleanly with transactional semantics. Moreover, we may not always wish that asynchronous function calls be part of the same transactional context. For example, checkout triggers a detached transaction add_store_visit, which is separately executed at a later time, to record a trace of store visits for the customer. In such a case, flexibility in fault tolerance guarantees can be afforded to the detached transaction for recording the purchase of the customer, since independent failure of a customer actor does not preclude the main application functionality from being executed. Similarly, add_items might not need durability since it can be recomputed from the cart’s physical contents albeit with different prices and fixed discounts (if inventory or group manager prices and discounts change) depending on application semantics. Finally, asynchronicity also has implications on declarative querying functionality. While queries to the state of an actor are synchronous, the semantics of multi-actor queries involving asynchronous function calls needs to be carefully considered.

3 WHY ACTOR DATABASE SYSTEMS NOW?

In this section, we outline the technological and application design trends that act as key enablers for the use of actor database systems.

3.1 Popularity of Cloud Computing Platforms, Middleware and Microservices

The last decade has witnessed a massive growth in the amount and variety of web services, which have targeted cloud computing infrastructure for deployment. Utilizing a three-tier architecture, these services employ a stateful middle tier using web-application frameworks or language runtimes, while the data tier consists of
Figure 1: Actors in the data tier of a simplified IoT smart supermarket application. The cart actor supports two transactions, namely add_items and checkout. Several functions are invoked in response to the add_items transaction (1). Both get_customer_info and get_price are asynchronously invoked on the customer and multiple store section actors, respectively (2). Once the customer marketing group is obtained, then get_fixed_discounts is invoked on the group manager actor (3). On checkout (4), get_variable_discount_update_inventory is invoked on each store section asynchronously (5). Finally, a detached transaction add_store_visits is invoked for later execution on the customer actor to record the store visit (6).

a database system. Web-application frameworks employing asynchronous and reactive programming, actor runtimes and NoSQL data stores have seen widespread adoption for constructing these interactive web services. Increasingly, application logic has been moved away from the database system into the middle tier, repurposing the database system as a fault-tolerant, consistent storage layer. Originally, this migration of logic to the middle tier was a response to scalability and performance concerns of the data tier, but of late programming flexibility and development productivity have emerged as major drivers [42, 50, 51].

However, this approach has not been without its share of failings. The lack and misunderstanding of data consistency semantics, fault-tolerance models, and query capabilities in the middle tier have affected application correctness [13, 25], which has raised voices for integrating database features into middle tier platforms [18]. The growth of microservices as an architectural pattern has made a case for a modular, scalable, fault-tolerant design of these web services to avoid the pitfalls of a monolithic architecture [32]. However, current deployments of microservices argue for containerization of whole software components, which raises the operational cost of these services and burdens the application to administer and integrate these modular software systems.

Actor database systems have the potential to address all these existing gaps. They provide a concrete programming paradigm to functionally decompose the data tier in modules across actors in line with the microservice architecture, but at a logical level independent of actual software system components and without paying a high overhead for modularity and encapsulation. They also incorporate well-understood, decade-strong data management and fault-tolerance guarantees, which relieves developers from the burden of reasoning about complicated state consistency semantics under asynchronous, concurrent executions of application programs in the presence of failures. In short, actor database systems increase the programmability of the data tier, which can then be conceived as a language runtime with robust state management features instead of just a storage abstraction.

3.2 Modular, Elastic, Available and Heterogeneous Applications

The popularity of microservices points to the importance of a modular design as a solution to manage application complexity and failures. A modular design helps in better fault isolation, debugging and profiling of the individual modules as opposed to a monolithic design, thus increasing programming productivity. In addition, a modular design can improve availability by a fail-soft strategy,
where faulty modules and its dependents can be made unavailable instead of an entire application. A modular design also aids in targeted monitoring of the modules and better analysis of impacts, which can bring substantial benefits in load provisioning and resource utilization with workload changes. The latter has a direct impact on supporting elasticity for an application, which has become important today given the 24×7 nature of online web services and the changes in workload they go through.

Modularity is also an important building block in supporting the heterogeneous requirements of current web services. For example, an application might have varying durability needs where (1) the entire data need not be durable and/or (2) only executions of certain programs need to be durable. Another case can be made for encrypted data where the entire data need not be encrypted and engender the associated overheads. Similarly, a case can be made for concurrency control, where different subsets of data and programs can benefit from different concurrency control structures and isolation levels. Currently, these heterogeneous needs are explicitly managed by the application by deploying associated software components, which significantly increases application complexity and maintenance overheads.

Actor database systems with their modular, concurrent and fault-tolerant programming model can cater to these application needs in a manner that is both more natural and better integrated with data management functionality. By allowing decomposition across actors and supporting actor heterogeneity, actor database systems can allow application programmers to declare the durability, encryption and concurrency needs of each actor, thus making such actors the islands of homogeneity in the application.

3.3 Increasing Parallel Hardware

Over the past two decades, computing power has increased dramatically. Initially, this increase came in the form of higher clock rates for processors; of late, in the form of more processing elements (cores) in a single chip. The cost of these computing elements has gone down dramatically as well, making them widely affordable. Dropping costs and improving performance have also been witnessed in storage and networking technologies, which has given rise to new challenges for database systems to transition these hardware benefits to applications [7]. Even though database systems lie at the cross-section of system software (OS) and application programs, they lack abstractions to expose the available physical parallelism using a high-level programming model.

To this end, actor programming models hold promise to fill this gap, as they possess: (1) well-defined concurrency and asynchronous message passing semantics, and (2) a function-shipping programming paradigm. Actors allow for portable specification of applications in terms of high-level, application-defined concurrent computational elements independent of the actual physical hardware and operating system primitives. With an actor-based specification, the available control-flow parallelism in application functions can then be leveraged from a higher level of abstraction to improve application performance. Additionally, actor database systems can exploit the locality information encoded in actors to better target classic data management optimizations, e.g., for index structure layouts, code generation, and transaction affinity.

3.4 Latency Sensitive Applications

The last few years have witnessed a rapid growth of stateful, scalable, latency-sensitive web services in various application domains, e.g., online games, mobile and social payment platforms, financial trading systems, and IoT edge analytics [42, 50]. The increasing adoption of scalable actor runtimes such as Akka, Erlang and Orleans to deploy these services points towards the attractiveness of actor programming models for designing these applications [51]. By providing single-threaded execution with asynchronous message passing semantics, actors simplify concurrent programming while enabling developers to leverage available asynchronicity in the design of latency-sensitive and locality-aware applications.

However, actor runtimes shift the responsibility for state management under failures to the programmer, which has raised the need for integrating classical database state management functionality [18]. The data model in these runtimes is low-level, language-dependent and lacks declarative query capabilities, thus pushing physical design decisions into applications.

Actor database systems have the potential to simplify application development and portability without compromising programming flexibility and correctness in this growing space of stateful, latency-sensitive applications. To this end, actor database systems provide robust state management guarantees as well as high-level data model and query capabilities, bringing physical data independence to the actor programming model.

3.5 Security Risks

With increasing pervasiveness of software services, security challenges faced by these services continue to grow dramatically. These challenges include issues pertaining to data integrity, access control, authorization, monitoring and auditing of these services. It is equally important to detect security violations and to mitigate them with minimum possible impact on the service operation. With increasing size of application deployments and complexity, it is imperative that software tools support specification of secure application code and help in static and dynamic verification.

Actor database systems open up new possibilities to re-think the database security model for current and future applications. For example, the traditional security model based on users and roles can be augmented in actor database systems with object-capability security, aiding in monitoring information flow on message passing. Having a modular architecture can also enable auditing of security violations and upon incidents, help in limiting unavailability to only the affected actors and/or functions instead of all actors and all functions.

4 ACTOR DATABASE SYSTEM TENETS

In this section, we outline the tenets that identify an actor database system based on the analysis in Section 3. We further enumerate and classify the actor database system features under these basic tenets. We propose mandatory features that we envision a system must support to qualify as an actor database system and meet the design trends of interactive data-intensive applications. However, we do not consider this feature set as final, but as a concrete formulation for further discussion in the community. We additionally list a set of optional features that were part of our reflections in Appendix A.
4.1 Overview

Tenet 1: Modularity and Encapsulation by a Logical Actor Construct. In order to tackle growing application complexity, isolate faults, define heterogeneous application requirements and increase programming productivity, modular programming constructs providing encapsulation are required. It is also desirable that the overhead of modularity be as low as possible and that modules be defined by the application independently of the hardware and software used for deployment. Actors provide this low-overhead computational construct in an actor database system as opposed to objects, which are a data encapsulation mechanism only.

Tenet 2: Asynchronous, Nested Function Shipping. For latency-sensitive applications to leverage the benefits of increasingly parallel hardware, asynchronicity in communication among actors becomes necessary. By using asynchronous function shipping to communicate with an actor and by utilizing nested invocations of such asynchronous functions, an application can leverage the available application control-flow parallelism to minimize latency, increase locality of data accesses in functions, and thus improve application performance using high-level programming abstractions.

Tenet 3: Transaction and Declarative Querying Functionality. In order to ease the burden of managing complexity and to increase programming productivity, a well-defined model for concurrency and fault-tolerance is desirable. Single-threaded execution semantics in actor models has been extremely appealing to programmers, hinting at the potential of borrowing and adapting classic database mechanisms such as transactions and more specifically nested transaction models [56]. Moreover, to bring physical data independence to actor models, a high-level data model and declarative query capabilities are required for easy interaction with encapsulated state within the actors.

Tenet 4: Security, Monitoring, Administration and Auditability. In order to address security threats, support for limiting information flow is required from the programming model during design and construction of applications. In addition, at runtime, monitoring, administration and auditing components provide for further manageability of security violations. By virtue of modularity and encapsulation in actors, a host of language-based security techniques can be provided to enrich the programming model to reason about encapsulated state within the actors.

Tenet 5: Security, Monitoring, Administration and Auditability. In order to address security threats, support for limiting information flow is required from the programming model during design and construction of applications. In addition, at runtime, monitoring, administration and auditing components provide for further manageability of security violations. By virtue of modularity and encapsulation in actors, a host of language-based security techniques can be provided to enrich the programming model to reason about encapsulated state within the actors.

4.1 Overview

Tenet 1: Modularity and Encapsulation by a Logical Actor Construct

Mandatory Feature 1: Logical, Concurrent, Distributed Actors With Location Transparency. For modularity, an actor database system must provide a programming abstraction of concurrent and distributed logical actors. A logical actor is an application-defined processing entity that communicates using message passing. Messages can be modeled as a computation that causes a response (see Tenet 2). Logical actors are concurrent and distributed because every logical actor is isolated from each other and can run at the same time independently. A logical actor does not imply a one-to-one mapping to an actual physical element (e.g., thread or process) used to implement it, but is merely an application modeling construct.

Even though logical actors communicate via message passing, we define a logical actor to not have a mailbox abstraction as a traditional actor [3]. Hence, a logical actor must not be conceptualized as an interrupt handler where the application developer needs to implement the message receiving loop. Rather, a logical actor is a reactive entity that processes requests submitted to it from clients or other logical actors. The decision to make logical actors reactive does not preclude the use of application-defined mailboxes, but does not force this design onto every application over an actor database system.

The application developer can model and structure her application with logical actors as in Figure 1. Note that the relations displayed in the figure could have been alternatively grouped under a different actor design. Consequently, a given application can be structured in multiple ways depending on how logical actors are defined. We envision that a logical actor would be understood by developers as a logical thread of control and used to capture the units of scaling and available parallelism of the application. For example, the whole set of logical actors in Figure 1 could be instantiated once per store or group of stores. At finer granularity, the application could be scaled on the number of carts and sections within a store.

A logical actor primitive can be provided in multiple ways. An object-oriented abstraction [16, 23] can be used to provide a logical actor primitive where the methods of the object define the computations that can be invoked on the logical actor. A function-oriented primitive can also be used by just declaring the logical actors and then defining computations in terms of them. In contrast to objects in object-oriented database systems [10], however, actors in actor database systems are not simply an abstraction to encapsulate data and define behavior on it. Logical actors provide the illusion of a thread of control and thus allow the developer to explicitly model the scalable units of her application as well as asynchronous computation and communication as discussed in Tenet 2. Logical actors allow decomposition of the data tier in a modular fashion allowing for better isolation of bugs, containment of failures, and management of application complexity.

Every logical actor must be uniquely identified by a name. In other words, a logical actor must be assigned a name from a logical namespace by the application. The name of a logical actor acts as the logical actor’s sole identity from a programming perspective. For example in Figure 1, the name of a customer actor is the implicit primary key of the \texttt{customer\_info} relation, i.e., the customer ID.

Mandatory Feature 2: Actor Lifetime Management. Since the programming model exposes primitives for specifying application-defined logical actors, a natural question is whether the application needs to manage the life cycle of these actors. Traditionally, actor models have exposed actor lifetime management to the application. However, an actor database system can either choose to manage actor lifetime itself or delegate it to the application by selecting any of the following mechanisms:

1. Dynamic Actor Creation: Similarly to dynamic memory allocation, the application can be given the control to create and destroy logical actors dynamically. An attempt to create a duplicate logical
actor or to destroy a non-existent logical actor must be signaled by appropriate errors. This policy is similar to the model supported by existing actor language runtimes, such as Akka [4] or Erlang [9, 29].

(2) Static Actor Creation: An actor database system can also choose to manage actor lifetime itself and therefore not provide primitives for actor creation and deletion. In this mechanism, the actor database system creates the illusion of logical actors to be in perpetual existence to the application. This can be supported by (a) automatic actor creation [23], where accessing an actor by name automatically creates that actor; or (b) declarative actor creation, where the application declares the names of the logical actors that should be available for the lifetime of the application.

Tenet 2: Asynchronous, Nested Function Shipping

**Mandatory Feature 3: Asynchronous Operation Support.** Asynchronous messaging is necessary as a communication mechanism for logical actors to provide a programming construct for the application developer to reason about control and data flow dependencies and explicitly expose parallelism in a computation for performance. Asynchronous messaging across actors can be implemented in various ways, e.g., using traditional actor model message passing [2], or method invocations on objects returning promises [23], to name a few. Irrespective of implementation mechanism, asynchronous logical actor messaging must allow the callee to synchronize on the result of the communication if desired, i.e., if the communication is a send primitive then the client can choose to wait until the message is successfully received; similarly, if the communication is through a remote procedure call, then the client can choose to wait until its result is propagated back. For example in Figure 1, the functions get_customer_info and get_price are invoked asynchronously within the add_items transaction. Similarly, multiple calls to add_variable_discount, update_inventory are invoked asynchronously within checkout. By introducing asynchronicity in the messaging mechanism, the illusion of a purely sequential program is broken. Racy computations may now be possible, i.e., in the absence of any concurrent computation and given the same input state, the program execution can produce inconsistent result states depending on the order in which asynchronous computations are scheduled on a conflicting data item. Either the programming model must disallow statically the formulation of such programs or the runtime must reject such malformed programs. In addition, the impact of asynchronous messaging on the isolation semantics exposed by the programming model of an actor database system must be clearly defined.

Tenet 3: Transaction and Declarative Querying Functionality

**Mandatory Feature 4: Memory Consistency Model.** An actor database system must provide primitives to allow an application to control the isolation level across concurrent computations. Although enforcing before-or-after atomicity (serializability) of computations on the union of the states of all actors in an actor database would be the simplest isolation level to program with in order to guarantee correctness, evidence suggests that applications can tolerate lower isolation levels with alternative guarantees and mechanisms [13, 46]. At the same time, and in contrast to microservice architectures [32], actor database systems should not shy away from defining consistency semantics for global state manipulation across multiple actors.

Isolation levels and their control can be provided in various ways: (1) Borrowing traditional database isolation levels and exposing them as annotations in actor computations; (2) Following a turn-based model similar to Orleans [16]; (3) Employing application-defined invariant-based isolation guarantees [12, 46]. In all of these alternatives, isolation in sub-computations of a given computation must be considered carefully. For example, the isolation level of a parent computation could be propagated to child computations, the child could remain independent of the parent, or isolation level for the parent and the child computations should be compatible.

**Mandatory Feature 5: Fault-Tolerant Actors With Application-Defined Durability.** An actor database system must free the application developer from worrying about partial alteration of actor state by an incomplete computation under failure. Consequently, an actor database system must support the classic notion of all-or-nothing atomicity of computations (recoverability). Still, detached transactions running independently from a calling transaction should be provided to allow for flexibility in fault-tolerance guarantees and performance. For example, the logic of the add_store_visit call in Figure 1 is executed as a detached transaction with respect to checkout. To establish a fault-tolerance contract in the call, an exactly-once qualifier could be added to the add_store_visit invocation. Different detached transaction invocations may have different qualifiers, e.g., for at-most-once or at-least-once semantics.

In addition to recoverability, database systems guarantee durability of committed transactions. By contrast, actor runtimes do not provide any durability guarantees for computations, forcing the application developer to store either parts or the entirety of actor state in an external storage system. To allow flexibility of application design, the programming model of an actor database system must fall in-between the two extremes and allow an application to control actor state durability. The logical programming model must thus support the notion of durability as a property to avoid contamination with physical deployment as is the case in actor systems. For example in Figure 1, the application may choose not to make the cart actor durable, since it can always be reconstructed if needed by reading the contents in the physical shopping cart itself. Alternatively, durability annotations could be specified per computation and not per actor. In contrast to early systems such as Argus [38], however, such mechanisms must work in conjunction with a high-level data model and declarative querying, as discussed in the following features.

**Mandatory Feature 6: High-Level Data Model and Declarative Querying Support.** The state of a logical actor must be abstracted by a high-level data model to provide for physical data independence. An application developer should have full freedom in defining the schema of a logical actor fitting the application needs, thus allowing schema definitions to vary across logical actors. This allows the application in Figure 1 to specify appropriate schemas in the relational...
model for the different actors, and frees the application developers from worrying about the physical data layout. The actor database system must also provide a declarative query facility over the state encapsulated in a single actor. This query facility provides ease of programming and allows for reuse of existing database query optimization machinery for performance.

**Mandatory Feature 7: Multi-Actor Declarative Querying.** Declarative querying in an actor database system must extend to multiple actors. Multi-actor query support could be added by prepending actor names before relations, objects, or other data model constructs similarly to object-oriented query languages [6, 37]. However, this simplicity is elusive: as opposed to object models, the actor model includes explicit asynchronicity in any multi-actor accesses, which must happen through message passing or function calls. Thus, the semantics of asynchronous execution of computations needs to be reconciled with the simplicity of a declarative interface. In addition, query optimization needs to be revisited to take into account asynchronicity elements in query specifications.

**Tenet 4: Security, Monitoring, Administration and Auditable**

**Mandatory Feature 8: Actor-Oriented Access Control.** Actor encapsulation and modularity provide security by ensuring that an actor’s state can only be accessed through its methods and by localizing security breaches. This enables standard static verification of illegal accesses by information flow analysis. However, this mechanism can be enriched further with access control features found in classic RDBMS, in particular fine-grained access control models [35, 44]. Such an integration would allow, for example, rich access specifications by methods of actor types and/or particular actor names to other methods of actor types and/or given actor names. By allowing both static and dynamic configuration of access control, static verification and debugging utilities can enrich the design process while dynamic changes protect against violations at runtime. In addition, to further protect against unauthorized access, actors should allow specification of encrypted relations in their state and annotation of methods as encrypted to ensure all communication to and from the methods are encrypted as well.

**Mandatory Feature 9: Administration and Monitoring.** An actor database system should also provide an administrative interface for flexible maintenance, allowing addition and removal of actors, changing resources allocated to them and modifying access control specifications. Furthermore, an actor database system must support targeted monitoring of actors by gathering statistics of actor usage as well as audit traces of actor method executions, potential security violations, and anomalous accesses. Taken together, this functionality enables administrators to intervene in the system at a fine granularity, e.g., removing or deactivating specific actors that are detected as exhibiting malicious behavior.

## 5 CASE STUDY: SMARTMART

In this section, we perform a case study of the smart supermarket application outlined in Figure 1 and briefly described in Section 2 in light of the enunciated tenets and the feature set in Section 4. We revisit each of these tenets and features to provide a concrete example of each in the context of this application.

### 5.1 Application Logic Overview

The SmartMart application models interactions in a supermarket where carts are equipped with sensors to read the physical cart contents and to trigger checkout operations. These sensors periodically interact with the back-end service in the data tier to call `add_item` and `checkout`. In a real application, more operations, such as to remove items from the cart, need to be supported, but we omit these additional operations for brevity.

In the application, the discount available on an item is classified into two components: (1) fixed discount and (2) variable discount. The fixed discount is customized for a marketing group of customers, while the variable discount is computed based on the demand for the item over a predefined window. Every item has a minimum price as well to ensure that discounts do not overshoot it. The price and fixed discount are computed when items are added to the cart, while the variable discount is only computed at checkout. For an item `i`, if `q_{i, t}` represents the quantity bought at time `t` and `S_{i, t}` represents the set of quantities from the reverse purchase history of the item starting at `t - 1` and size at most `k`, then the variable discount is computed using the following formula:

\[
vdisc_{i, t} = \frac{q_{i, t}}{\mu(S_{i, t}^k)} + c \times \sigma(S_{i, t}^k) \times VD_i
\]

For a tunable and predefined constant `c`, the denominator in the fraction models a target purchase quantity from the history of purchases based on the mean plus `c` standard deviations of the purchase quantity distribution. `VD_i` is the predefined variable discount that such a purchase would receive. Thus, the current purchase is normalized by the target purchase and then multiplied with `VD_i` to compute the dynamic variable discount.

### 5.2 Tenet 1

According to Feature 1, an actor database system must provide a construct to create logical actors. In Figure 2, the keyword actor is used to specify two application-defined actor types, namely (1) `Customer` and (2) `Group_Manager`. An actor type definition must also include the encapsulated state using the supported data model, which is bound to the lifetime of the actor. In the example, the state has been abstracted using relations, whose schema definition is omitted for brevity.\(^1\) Each actor type also defines the set of methods that can be invoked on the actor. In contrast to methods in classic object-based models, actor models explicit define that method calls must be logically shipped for execution on the desired actor, since each actor is a logically concurrent entity. Furthermore, the state encapsulated in each actor can only be accessed by invoking methods defined by the actor. An actor method can contain any sequence of queries, procedural logic and invocations to other actors. Any variable defined in actor methods and not in the state has the lifetime of the method only and not the actor.

In line with Feature 2, an actor database system must provide automatic actor lifetime management. For example, in a system supporting static declarative actor creation, commands to create and delete actors should be provided to support actor creation and deletion.

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\(^1\)The full pseudocode for the example is available in Appendix C. For all code examples, we make simplifications in type annotations and conversions to keep the pseudocode brief.
we abstract method invocations on actors as asynchronous function invocations. According to Feature 3, an actor name can be any application-defined string. The calling code can synchronize on the future by invoking get when the value is needed. For example, this is done to obtain the result value from the get_fixed_discounts method call. Alternatively, multiple futures can be synchronized upon at the same time by calls such as when_all or when_one to consume result values when all or any one are available, respectively. In the example, the futures from the price lookups are synchronized upon using the barrier semantics (when_all), after which cart purchases are recorded and an updated session ID value is returned for later use during checkout.

**5.3 Tenet 2**

According to Feature 3, an actor database system must support nested asynchronous function shipping. To exemplify this feature, we abstract method invocations on actors as asynchronous function calls returning futures, which represent the result of the computation. In Figure 3, we illustrate how method invocations and result synchronization could be operationalized in an application program. The figure shows the pseudocode of the add_items method in the Cart actor. For simplicity, we assume that the cart is private for a customer, and the method is only invoked once for all the items ordered in the cart before a checkout is performed. Within the pseudocode of add_items, further method invocations to other actors are performed. An invocation of a method on an actor must specify the type of the actor within the <> brackets and the name of the actor within the [ ] brackets, followed by the method and its arguments. For example, in the first loop in the program, we invoke the get_price method on each of the store sections in the item orders. The call is directed to an actor of type StoreSection, whose name is given by the section ID. The method gets as argument a list of the items across all item orders for the corresponding section ID. As a result, the method call produces a future. All futures are collected in a map for synchronization at a later time. As such, the subsequent logic in add_items is executed while the asynchronous calls to get_price are processed.
5.4 Feature 3

Feature 4 specifies that a memory consistency model must be defined by an actor database system to clarify the semantics of multiple method invocations on the same actor and across actors. While multiple memory consistency models are possible, in our example we adopt classic database serializability, and propagate this same isolation level across all nested method invocations. This simplifies the application code in Figures 3 and 4, since the application developer is insulated from concurrent and asynchronous manipulation of actor state within and across multiple transactions. Furthermore, in order to maintain well-defined results under asynchronicity, any two conflicting sub-computations on the same actor must be ordered by the application code via synchronization using futures; otherwise, the actor database system aborts the entire computation.

In line with Feature 5, we adopt all-or-nothing atomicity of methods and application-defined durability per actor in our example. All-or-nothing atomicity frees the developer from worrying about partial state changes encapsulated by one or many actors, and thus frees the application logic from implementing failure-handling code as in Figures 3 and 4. Application-defined durability per actor allows flexible specification of durability requirements. In the example, the Cart actor is annotated as nondurable, while the other actors are durable by default. So, all state manipulation of committed transactions is durable on the Customer, Group_Manager and Store_Section actors only. This allows the application to flag cart state as transient, while not giving up all other data management features in implementing cart operations.

In addition to durability annotations, the notion of detached transactions allows for invocations of sub-computations in a separate transactional context, i.e., the sub-computation does not share the isolation level and atomic commitment requirements of the callee [41]. The callee can specify when the detached computation should be invoked, e.g., on successful commit of the callee, abort of the callee, or any of them. This feature has been used in Figure 4 to invoke a detached transaction on the customer actor so as to record purchase information on successful commit of checkout.

According to Feature 6, a high-level data model and declarative state querying capabilities must be provided. In Figure 4, cart_info exemplifies a relation schema abstracting portion of the encapsulated state of the actor type Cart. The method checkout interacts with the encapsulated cart_info and cart_purchases relations using declarative queries in SQL.

Figure 4 also exemplifies Feature 7, since declarative multi-actor querying is employed in contrast to the use of imperative constructs and explicit future synchronization in application code in Figure 3. The figure shows a SQL query that invokes get_variable_discount_update_inventory in all store sections that have participated in the given session. The list of items passed as input to each invocation is constructed by converting the relational result of a nested query to a list by function LIST. The result of the invocations is a relation with price and discount information per store section. This result is aggregated in the top-level SQL query to compute the total amount bought along with total fixed and variable discounts for the checkout.

5.5 Tenet 4

By Feature 8, actor-oriented access control should enrich traditional object-based access modifiers with fine-grained access control as studied in database systems. In the SmartMart example,
suppose we wish to configure minimum levels of access to mitigate security risks so that: (Rule 1) \text{add\_items} in \text{Cart} actors has access to \text{get\_price} in \text{Store\_Section} actors, \text{get\_fixed\_discounts} in \text{Group\_Manager} actors and \text{get\_customer\_info} in \text{Customer} actors; (Rule 2) \text{checkout} in \text{Cart} actors has access to \text{get\_variable\_discount\_update\_inventory} in \text{Store\_Section} actors and \text{add\_store\_visit} in \text{Customer} actors; and (Rule 3) A set of specific cart instances (e.g., carts 12, 13, and 14) can only interact with the sections of their corresponding physical store (e.g., store sections 100 and 200). This access configuration can be enforced in an actor database system by the following commands:

\begin{verbatim}
REVOKE ACCESS TO ACTORS OF TYPE ALL FROM ACTORS OF TYPE ALL;

GRANT ACTORS OF TYPE Cart WITH METHODS IN (add_items) ACCESS TO
ACTORS OF TYPE Store_Section WITH METHODS IN (get_price)
AND ACCESS TO
ACTORS OF TYPE Customer WITH METHODS IN (get_customer_info)
AND ACCESS TO
ACTORS OF TYPE Group_Manager WITH METHODS IN
(get_fixed_discounts);

GRANT ACTORS OF TYPE Cart WITH METHODS IN (checkout) ACCESS TO
ACTORS OF TYPE Store_Section WITH METHODS IN (get_variable_discount_update_inventory)
AND ACCESS TO
ACTORS OF TYPE Customer WITH METHODS IN (add_store_visit);

GRANT ACTORS OF TYPE Cart WITH NAMES IN (12,13,14) ACCESS TO
ACTORS OF TYPE Store_Section WITH NAMES IN (100,200);
\end{verbatim}

The first \text{REVOKE} statement revokes access rights of all actors to each other. The next \text{GRANT} statement configures Rule 1 for access privileges of \text{add\_items}, while the next statement configures Rule 2 for access privileges of \text{checkout} in the \text{Cart} actor type. The final statement additionally sets up a rule by actor name to enforce Rule 3. The previous rules, which are configured by actor types, can additionally use the \text{WITH NAMES} clause to configure even finer granularity of access. Taken as a whole, the set of rules must cleanly compose or otherwise be flagged and rejected. The set of configured rules can be used for static verification and debugging of security violations. In addition, modification of these rules during deployment enables dynamic adaptivity of security policies to meet unforeseen security threats, e.g., by revoking rights from selected actors.

Since the application functionality is deconstructed in terms of actors, \textit{Feature 9} implies that the actor database system should provide monitoring of actor usage and resource utilization (e.g., some store sections being more loaded than others), security violations (e.g., a \text{Group\_Manager} actor attempting to access a \text{Store\_Section} actor), and audit traces (e.g., traces of \text{checkout} and nested method invocations). It also implies administrative support to scale actors and resources to meet usage fluctuations discovered during monitoring, or change access control specifications based on security violations, to name a few possibilities.

### 5.6 Evaluation: Asynchronicity + Transactions

In this section, we evaluate: (1) The potential for performance gains provided by asynchronous communication in actor databases (Section 5.6.2); and (2) The effect of load under concurrency on transactions with asynchronicity (Section 5.6.3).

#### 5.6.1 Experimental Setup

We present the hardware, workload, system prototype, and methodology used for the evaluation.

**Hardware.** We employ a machine with two sockets, each with one eight-core 2.6 GHz Intel Xeon E5-2650 v2 processor with two physical threads per core, leading to a total of 32 hardware threads. Each physical core has a private 32 KB L1 data and instruction cache and a private 256 KB L2 cache. All the cores on the same socket share a last-level L3 cache of 20 MB. The machine has 128 GB of RAM in total, with half the memory attached to each of the two sockets, and runs 64-bit RHEL Linux 3.10.0.

**Workload.** We used the SmartMart application for our experiments. To simulate the workings of one store, we created eight \text{Store\_Section} actors. For each, we loaded the inventory relation with 10,000 items and the \text{purchase\_history} relation with 300 entries per item for a total of 3,000,000 entries, simulating a history of 120 days where 500 customers on average visit the store per day and buy 50 items each. We fix the number of \text{Group\_Manager} actors to 10 and vary the number of \text{Cart} actors depending on the experiment. The number of \text{Customer} actors is set to 30 times the number of carts. To calculate the variable discount, we tuned the window size to correspond to 150 records in the \text{purchase\_history} relation, thus calculating a target purchase quantity over 60 days (Equation 1). The entire size allocated after loading was \textbackslash ~3 GB.

**System Prototype.** We run our experiments in an actor database system prototype (\textsc{ReactDB}) [48] with basic implementations of Features 1 to 4. Actors are allocated to thread pools pinned to cores, and all actor state is stored in index structures under optimistic concurrency control (OCC) in Silo [55]. Method invocations on actors provide serializability. We configured the prototype in two modes, namely: (1) \textit{sync}: all the method invocations across actors are executed synchronously and in the same thread to represent sequential execution; and (2) \textit{async}: a method invocation on a \text{Store\_Section} actor is dispatched to the thread pool representing the actor for execution using a queue. We ran our experiments without any durability of transactions. We tuned the thread pool sizes to minimize queuing delays and maximize usage of physical cores.

**Methodology.** We map each \text{Cart} actor to the thread pool pinned to each of the eight physical cores in the first socket. We allocate worker threads such that each worker thread generating method invocations on a \text{Cart} actor is mapped to the hyper-threaded core of the corresponding cart to simulate client affinity. For \textit{async}, all actors except of type \text{Store\_Section} that are involved in a cart transaction are local to same core as the cart, and accessed synchronously. Invocations to methods of \text{Store\_Section} actors, however, are dispatched for asynchronous execution. Each of the \text{Store\_Section} actors are mapped to thread pools pinned to each of the eight physical cores on the second socket.

A worker runs interactions consisting of \textit{add\_items} and on its successful commit \textit{checkout}. We measure the average latency and throughput of the entire interaction using an epoch-based measurement strategy [27]. Each epoch consists of 2 sec, and we report averages and standard deviations of successful interactions over 20 epochs. Workers choose customer IDs from a uniform distribution. The items and store sections in orders are also chosen from a uniform distribution for a configurable number of store sections and items per store section in the order.
5.6.2 Leveraging Asynchronicity in SmartMart. To more clearly observe the gains offered by asynchronicity, we first study the effect of increasing both work and asynchronicity in method calls from a single worker. We vary the number of store sections from 1 to 8 while keeping the number of items ordered from each section fixed at 4, thus varying the size of the order from 4 to 32. Figure 5 shows that the throughput of sync degrades with increasing order size given the sequential execution of the methods. The slope of the curve also decreases with store sections since the increase in the order size is constant, and hence has a smaller impact as the order size grows. By contrast, async has lower throughput when the number of store sections is one, but reaches 3.2x higher throughput than sync for 8 store sections. At the beginning, async suffers from lack of sufficient asynchronicity and overhead of dispatch to the Store_Section actor as opposed to shared memory accesses in sync. However, as the number of store sections increases, asynchronicity benefits arise since the variable discount computations across store sections during checkout and price lookups during add_items are overlapped to utilize parallel resources.

5.6.3 Effect of Load on Asynchronicity. By gradually increasing the number of concurrent workers, we study the effect of load on the benefits of asynchronicity observed above. We keep the work fixed to an order size of 32, corresponding to an order across 8 store sections and 4 items from each store section, and increase the number of workers, carts and customers in the experiment. Figures 6 and 7 show the throughput and latency observed. While sync exhibits excellent throughput and latency scalability as we increase the number of workers, the throughput of async scales well until three workers and then degrades before roughly stabilizing. This is because at three workers the Store_Section actors are close to full resource utilization (CPU core at 88%), maxing out at four workers and then becoming the bottleneck. The resulting effect of queuing can also be seen in the latency measurements, where the latency increases dramatically after four workers.

Despite the queuing effects, async still outperforms sync because of the amount of physical resources being utilized by it, namely 16 cores with intra-transaction parallelism as opposed to 8 cores in sequential execution. We did not perform measurements for more than 8 workers, since the hardware does not have enough physical cores to sustain our setting for async. Nevertheless, we would expect a crossover with sync as load increases. In short, asynchronicity can bring both throughput and latency benefits over a traditional synchronous strategy when load in the database is light to normal and transactions exhibit parallelism.

During this experiment, we observed abort rates of ~5-7% despite the small amount of actual logical contention on items. This happens because the OCC protocol of Silo aborts transactions if the version numbers of nodes scanned change at validation time, caused in our experiments by tree splits due to inserts.

6 RELATED WORK

Actor languages and frameworks. Actors were proposed as a model for concurrent computations centered around a message passing semantics [2]. Actors encapsulate state, provide single-threaded semantics for message handling and hence state manipulation, and support an asynchronous message shipping programming paradigm. Because of these concepts, actor languages and frameworks provide an elegant mechanism to model concurrent and distributed applications [4, 21, 29, 47]. However, managing actor lifecycle, handling faults and ensuring high-performance of actor runtimes in a distributed infrastructure complicates their usage, which has led to the appeal of virtual actors [23] for transactional middleware [17].

Despite advances in actor runtimes such as virtual actors, actors put the burden of state management on the application. Applications need to choose either main memory or using external storage solutions for actor state, depending on durability and fault-tolerance requirements. Applications are also forced to account for and handle the failure and consistency models of the underlying storage systems employed. Lack of all-or-nothing atomicity leads to complications in application code to ensure consistency of application state under failure.

By contrast, actor database systems offer the state management guarantees that classic databases have long provided under the notion of transactions to ensure application developers can focus on writing application logic. By providing well-defined state manipulation semantics in the presence of failures, actor database systems simplify construction of distributed, concurrent and stateful applications. In addition, actor runtimes lack a high-level data model along with declarative querying facilities, which actor database systems provide. Actor database systems are envisioned to abstract the data tier as a distributed runtime to increase its programmability and scalability, and not as a replacement of actor runtimes deployed in the middle tier as a soft-caching layer with high-availability and weak-consistency guarantees.
Microservices. Microservices have gained a lot of popularity recently as a software engineering paradigm [32]. Microservices advocate design of software systems as small, modular services that are deployed independently and communicate using a messaging mechanism. Each small, modular service can use an independent software stack. Actor database systems can be viewed as a programming paradigm to design the database tier of a software system using the microservice architecture by functionally decomposing the data tier in modules across actors. By allowing decomposition of the data tier in terms of actors, actor database systems provide a lightweight and resource-efficient primitive when compared with decomposition across multiple database instances as with existing solutions. One or many actor database systems can be used for deployment of the data tier depending on the needs of the application and its design.

Classic Relational Database Management Systems (RDBMS). RDBMS were designed to support declarative querying of data abstracted using a relational data model [33]. In order to shield the application developer from concurrent execution of application programs and hardware failures, ACID transactions became the de facto standard for RDBMS. At a high level, the programming model of a database is that of a single shared space, where access to data items is achieved using a declarative query language with transactional guarantees. As a performance optimization, stored procedures were introduced to co-locate a sequence of client queries in the database and reduce data transfer costs [45].

This programming model leads to a monolithic design of the data tier causing the following issues: (1) Since any part of the application logic in any stored procedure can access any data stored in relations, it becomes hard to isolate and identify bugs in application logic especially with growing size of data, numbers of relations and stored procedures, and with growing application complexity; (2) Since the entire data and logic are shared in the database, a failure causes unavailability of the entire database system instead of failure of the affected parts only; (3) Since the programming model lacks a notion of an active thread of control and consequently the notion of what constitutes an unit of scalability, it is hard to reason about the scalability of the database without understanding details of database system implementation. In contrast, by providing an actor-oriented primitive for state encapsulation and modularity, actor database systems provide an application-controlled mechanism to functionally decompose the database into modules. This mechanism allows application developers to manage code complexity, isolate bugs, contain failures, and reason about scalability of the database.

Partitioned RDBMS. Modern database systems employ database partitioning to deploy the database over different hardware deployment infrastructures, e.g., multiple machines or multiple cores in the same machine, and co-locate data with processing elements for performance. This technique is applied in database architectures for systems covering the extremes of shared-nothing [36, 53] and shared-everything [26, 34, 40, 55]. Despite the extensive use of data partitioning under the hood in these systems, the programming model introduced by classic RDBMS remains unchanged. As such, partitioned RDBMS also suffer from the same software engineering problems caused by the monolithic design of the data tier, since these systems are invariant in their programming model compared with classic RDBMS. In addition to solving the aforementioned software engineering issues, actor database systems provide a programming model that allows application developers to understand the performance issues with their design. Furthermore, asynchronous messaging between actors allows application developers to explicitly leverage intra-transaction (data and control) parallelism in arbitrary programs, and to reason about the relative performance of different programs depending on the level of parallelism employed.

Object-oriented Database Management Systems (OODBMS). ODBMS focused on addressing the impedance mismatch existing between RDBMS and programming languages [10, 15]. While persistent programming language runtimes tried to bring database support to popular object-oriented languages such as C++ [11], ODBMS such as O2 proposed an object-oriented data model with an embedded declarative query language [37]. ODBMS proposed object-orientation for modularity, data encapsulation, behavior specification and extensibility. However, objects in ODBMS do not have any notion of a thread of control, i.e. objects are not an active execution entity that can execute logic but rather they are an abstraction to encapsulate data and to define behavior on this data.

On the contrary, actors in an actor database system both encapsulate data and represent an active, concurrently executing entity with a thread of control. This allows for reasoning about locality and scalability in terms of the number of actors and their communication patterns with each other. Actor database systems support asynchronous communication primitives, which allows for specification of parallel programs spanning multiple actors. The latter is not possible with the synchronous method invocation semantics of objects in OODBMS. Actors in actor database systems can support any data model, e.g., the relational data model as advocated in this paper, while the data model is inflexible in OODBMS.

7 OUTLOOK AND CONCLUSION

This paper has made the case for actor database systems, a new data management approach combining the virtues of actor runtimes and classic databases. Actor database systems comprise logical actors with asynchronous operations as well as transactional features and declarative querying, providing for modularity, parallelism, fault tolerance, and security. We believe that actor database systems open up exciting research possibilities in various aspects of data management ranging from conceptual modeling to system design. A few of these possibilities are discussed further in Appendix B.

We argue that increasingly the world of interactive data-intensive applications will look more like the scenario depicted in Figure 1, where a combination of complex logic and data management is the norm. Instead of having database systems be relegated to persistent state management components in these applications, our call to the database community is for reimagining database programming models and architectures for this new world, and marry actors and database systems into a new abstraction.
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A OPTIONAL FEATURES FOR ACTOR DATABASE SYSTEMS

In this section, we list a number of features for actor database systems that we have classified as optional. The integration of these features promises interesting research challenges, but the need for their support based on interactive data-intensive application design trends is not as clear as for mandatory features. We refrain from classifying the optional features under specific tenets, since some of the features may have interactions with multiple tenets.
**Optional Feature 1: Actor Computational Heterogeneity.** The traditional actor model and its supported platforms advocate a notion of computational homogeneity, i.e., every logical actor has equal processing power [3]. However, in certain applications, some actors may have to sustain higher computation load than others. For example in Figure 1, a store section might have to sustain a higher load than a customer actor.

An actor database system can support programming constructs to allow the application developer to declare computational heterogeneity dependencies across actors, e.g., $\text{ActorX} > 2 \times \text{ActorY}$. These declarative specifications can be extended to express memory and communication requirements across actors as well. These logical actor computational relationships can then be leveraged in the actual deployment of logical actors on physical hardware to adapt to application load and to better specify and sustain application service level agreements.

**Optional Feature 2: Data Model Heterogeneity.** Given the growth in variety of data-intensive applications, it would be hard to presume that a single data model across all logical actors would suffice for all application needs. In order to provide more flexibility, an actor database system could allow disjoint parts of the state in and across actors to be abstracted by different data models (e.g., relational, object-oriented, XML). Such data model heterogeneity would allow for rich modeling of state within and across logical actors, avoiding re-architecting an application on top of a single data model. In contrast to recent proposals for polystores [28], however, an actor database system must provide the mandatory features discussed in Section 4. For example in Figure 1, the inventory and purchase history could be stored using an XML or object-oriented data model in the store section actor.

**Optional Feature 3: Language Integration and Computational Completeness.** One of the reasons for the popularity of NoSQL and MapReduce systems has been their mature integration with high-level programming languages, which makes it very productive for application developers to interface their application code with such systems. Therefore, tighter integration of programming languages in an actor database system is a desirable property. Since actor database systems aim at a large set of interactive data-intensive applications, an actor database system with a strong programming language integration providing computational completeness has a stronger appeal for adoption than one exposing a computationally incomplete domain-specific language embedding. Moreover, easy integration of the actor database system infrastructure with multiple target language dialects would increase the chances of adoption even further.

**B RESEARCH OPPORTUNITIES**

In this section, we outline research avenues in actor database systems organized under topical areas for better perspective.

**Theoretical Foundations.** With the introduction of actor database systems, interesting challenges arise on how to integrate logical actors, which are compute entities by essence, with the theory of database design and querying [1]. For example, the theory of data normalization has provided a measure of the quality of a database schema, with reduction of data redundancy being a key goal. With the introduction of actors, measures for the quality of a logical actor database (actors + schema) need to be defined. Intuitively, more actors would hint at a more scalable database design, but excessive distribution of application logic may lead to low efficiency. Such trade-offs need to be captured theoretically, and their consequences on the theory of normalization examined. In addition, it is an interesting challenge to formalize the notion of database constraints spanning the schema of relations in multiple actors. In the example of Figure 1, in order to ensure that the fixed discount does not exceed an item’s minimum price, we would need to specify a constraint spanning Group_Manager and Store_Section actors.

With the introduction of actors encapsulating state, the classical formalism of transactions also needs to be revisited. In [48], the authors introduce a model for formalizing transactions across actors, called reactors, as an extension to the classical transactional model [19], and prove that serializability of programs is isomorphic across the models. However, formalization of the semantics of detached transactions and of application-defined isolation levels for different child sub-transactions are also open problems that need further exploration.

**Conceptual Modeling.** The entity-relationship model has become the de facto standard for conceptually modeling the database [24]. The model is connected to a well-understood methodology for translating designs into corresponding database representations. With the introduction of actor databases, similar analytical machinery and associated tools are required to equip application developers with a methodology to model an application using actors.

**Programming Model and Query Support.** As pointed out in Tenets 2 and 3, actor database systems necessitate the integration of asynchronous programming with declarative querying. It is non-trivial to define proper query semantics and query optimization methods for this new scenario. Another interesting challenge for the programming model is the choice of query capabilities. To support tighter language integration, declarative query capabilities must be exposed by either using native language support or enhancing abstractions supported by the programming language. The space of complete declarative querying versus mixed declarative querying and imperative programming support, as well as the associated impacts on expressibility, productivity, and performance, needs to be explored and evaluated.

**System Implementation and Design.** Numerous challenges arise on efficiently designing and implementing systems for heterogeneous hardware architectures and cloud computing infrastructure while guaranteeing high resource utilization, scalable performance, and ease of programming. Two extreme approaches could be investigated. At one end of the spectrum, one could integrate database features into actor runtimes, starting for example from transaction support [54]. At the other end, one could add actor programming support into classical databases. For the latter, however, classical database components such as logging and recovery would need to be revisited in order to support application-defined durability. At the same time, such cross-cutting low-level mechanisms need to smoothly integrate with potential heterogeneity in actors due to type annotations and with asynchronous execution of methods across actors.

Actor database systems may also open up opportunities to re-architect database systems in new ways. By advocating a design
of an application using actors, an actor database system can now introduce a system architecture to virtualize a database across the extremes of shared-everything and shared-nothing at deployment, while keeping the programming model and application programs intact. In [48], the authors introduced an architecture to virtualize a database across the extremes of shared-everything and shared-nothing at deployment time, while keeping the programming model and application programs intact. As such, various deployment optimization problems can be further explored.

Software Engineering and Security. The introduction of actor database systems raises many interesting questions regarding the design of applications across the middle tier and the data tier. The set of design principles that should guide the placement of application functionality needs further exploration. In addition, implications on scalability, resource efficiency, consistency and availability can be explored by segmenting application functionality in different ways between the middle and data tiers. Moreover, the effect of an actor-oriented programming model in the data tier on code quality, i.e., number of bugs or ease of debugging and isolating failures needs to be explored. Furthermore, security models that integrate well with software engineering practices should be investigated. Emerging applications and traditional applications need to be modeled using actor database systems to understand and quantify the benefit of various programming model features.

C SMARTMART IMPLEMENTATION DETAILS

In Figures 8, 9 and 10, we present the pseudocode of the SmartMart application introduced in the main body of the paper. In the pseudocode, we make use of an additional conversion function TABLE to transform a list of values into a relation. The get_price method first computes a relation (rh) with the mean and standard deviation of purchase quantities for every item in the list of requested items (ord_items) for a statically defined history window size of K. This relation is then joined using an inner join with inventory and the relation representing the ordered items (TABLE(ord_items)) to get the necessary information required to compute the cumulative price and discounts to be returned for the order. Note that the minimum price has been accounted for in the price and discount computations. Subsequently, for each item in the order, the inventory is updated to reflect the purchase (and replenished if necessary), following which the purchase is recorded in the purchase_history relation.

Figure 10 shows the implementation of the Cart actor. The add_item method first constructs a list of item ids by store section from orders provided as input. For brevity in the pseudocode, we represented these data structure interactions as function calls, namely: (1) extract_arrange, (2) extract_ids, and (3) lookup. The method then invokes get_price method calls on each of the

Figure 8: Implementation of Group_Manager and Customer actors.

Store_Section actors asynchronously storing the futures in a map data structure for later synchronization. Declarative multi-actor queries were not used, because we want to overlap other subsequent computations in the body of the method in addition to the asynchronous get_price method calls across store sections.

After firing price lookups, the customer group is looked up using a declarative multi-actor query on the Customer actor. The customer group is then used to invoke get_fixed_discounts on the Group_Manager actor. Finally, synchronization is used to get the discounts and to wait for all price results to become available from store sections. Using imperative constructs, we iterate over the values of the price results (results). For each record in the map data structure, .first and .second are the handle to the key and the value respectively. For each store section ID (sec_id_res.first), we invoke get() on the future (sec_id_res.second) to get the price values of the items requested from that store section. Note that this call to get() returns immediately, since synchronization on all the futures has been done earlier with when_all(). We use the price information in conjunction with lookups in our input orders and fixed discount values (discounts) to then record an entries in cart_purchases for use during checkout.

The method checkout is explained in Section 5.4. The function is also included in the definition of the Cart actor in Figure 10 for completeness.
actor Store_Section {  
state:  
relation inventory (i_id int, i_price float,  
i_min_price float,  
i_quantity int, i_var_disc float);  
relation purchase_history (i_id int, time timestamp,  
i_quantity int, c_id int);  
method:  
list-tuple> get_price(list-int> i_ids) {  
return LIST(SELECT i_price, i_min_price FROM inventory  
WHERE i_id IN (TABLE(i_ids))):  
}
tuple get_variable_discount_update_inventory(  
int c_id, timestamp c_time, list-tuple> ord_items){  
SELECT SUM((CASE  
WHEN i_price > i_fixedDisc + i_var_disc  
THEN i_price - (i_fixedDisc + i_var_disc)  
ELSE i_min_price) * i_quantity) AS amount,  
SUM(i_fixedDisc - i_quantity) AS fixed_disc,  
SUM((CASE  
WHEN i_price > i_fixedDisc + i_var_disc  
THEN i_var_disc  
ELSE (i_price - i_min_price - i_fixedDisc)) * i_quantity) AS var_disc  
INTO v_totals  
FROM (SELECT ph.i_id, o.i_quantity,  
      o.i_quantity / (ph.i_avg + c * ph.i_stddev))  
+ inv.i_var_disc AS i_var_disc,  
      o.i_min_price, o.i_price, o.i_fixedDisc  
FROM (SELECT i.id,  
      AVG(i.quantity)  
OVER (PARTITION BY i.id  
ORDER BY time DESC  
ROWS BETWEEN CURRENT ROW AND K  
FOLLOWING) AS i_avg,  
      STDEV(i.quantity)  
OVER (PARTITION BY i.id  
ORDER BY time DESC  
ROWS BETWEEN CURRENT ROW AND K  
FOLLOWING) AS i_stddev  
FROM purchase_history  
WHERE i_id IN (SELECT i_id FROM TABLE(ord_items)) ph  
INNER JOIN TABLE(ord_items) o ON (o.i_id = ph.i_id)  
INNER JOIN inventory inv ON (inv.i_id = ph.i_id);  
}
foreach o_i IN ord_items {  
UPDATE inventory  
SET i.quantity = CASE  
WHEN i.quantity > o_i.i_quantity  
THEN i_quantity - o_i.i_quantity  
ELSE 10000  
WHERE i_id = o_i.i_id;  
INSERT INTO purchase_history  
VALUES (o.i_i_id, c_time, o_i.i_quantity, c_id);  
}
return v_totals;  
};

Figure 9: Implementation of Store_Section actor.

actor Cart {  
state:  
relation cart_info (c_id int, store_id int, session_id int);  
relation cart_purchases (sec_id int, session_id int, i_id int,  
i_quantity int, i_fixed_disc float,  
i_min_price float, i_price float);  
method:  
int add_items(list-order> orders, int o,c_id) {  
// Organize the items in orders by store section  
orders_by_store_section = extract_arrange(orders);  
map-int,future> results;  
for (section_order : orders_by_store_section) {  
future disc_res = actor>Store_Section>section_order.sec_id].  
get_variable_discount_update_inventory(  
LIST(SELECT i_id, i_quantity, i_price, i_fixedDisc,  
inventory)  
FROM cart_purchases  
WHERE session_id = s.session_id);  
results.add(section_order.sec_id, res);  
}
SELECT c.g_id INTO v.c.g_id  
FROM actor>Customer>get_customer_info()  
WHERE name = o.c_id;  
// Compute list of all ids of ordered items  
ordered_item_ids = extract_ids(orders);  
future disc_res = actor>Group_manager[v.c.g_id].  
get_fixed_discounts(ordered_item_ids);  
// Generate session_id and update cart_info  
SELECT session_id = 1 INTO v.session_id FROM cart_info;  
UPDATE cart_info  
SET c_id = o.c_id; session_id = session_id + 1;  
list-tuple> discounts = disc_res.get();  
results.value_list(when_all);  
// Iterate over prices and discounts and store in  
cart_purchases  
foreach sec_id_res in results {  
foreach i,p in sec_id_res.second.get() {  
fixed_disc = lookup(discounts, i.p.i_id);  
i.quantity = lookup(orders, i.p.i_id);  
INSERT INTO cart_purchases  
VALUES (sec_id_res.first, v.session_id, i.id,  
i.quantity, fixed_disc, i.p.minPrice,  
i.p.price);  
}
return v.session_id;  
}
}

float checkout(int c_session_id) {  
SELECT * INTO v.cart FROM cart_info;  
timestamp v.c_time = current_time();  
SELECT SUM(amount) amt, SUM(fixed_disc) fixed_disc,  
SUM(var_disc) var_disc  
FROM (SELECT SELECT amount, fixed_disc, var_disc  
FROM actor>Store_Section>  
get_variable_discount_update_inventory(  
v.cart.c_id, v.c_time)  
LIST(SELECT i_id, i_quantity, i_price,  
i_fixed_disc, i_min_price  
FROM cart_purchases  
WHERE sec_id = s.sec_id  
AND session_id = s.session_id)  
WHERE name = s.sec_id  
FROM SELECT DISTINCT sec_id  
FROM cart_purchases  
WHERE session_id = c.session_id) S);  
DETACH actor>Customer[v.cart.c_id].add_store_visit(  
v.cart.store_id, v.c_time, amt, fixed_disc, var_disc)  
ON COMMIT;  
return amt;  
}  

Figure 10: Implementation of Cart actor.