Real-Time Data Synchronization Optimization: A Comparative Analysis in Distributed E-Commerce Systems

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Abstract— **In the fast-changing environment of e-commerce, the requirement of real-time synchronization of data among different front-end applications and a centralized backend has become essential. This paper discusses the issues that lie in data management in distributed e-commerce systems and specifically emphasizes the synchronization of user interactions among multiple platforms such as customer interfaces and administrative portals. We examine three leading data handling algorithms: Event Sourcing, Change Data Capture (CDC), and Distributed Transactions, and explore their efficacy in maintaining data consistency, scalability, and fault tolerance. In a comparative analysis, we identify the strengths and weaknesses of each algorithm and offer insights into their viability in high- traffic e- commerce scenarios. Our results indicate that an event- driven architecture, together with the proper data handling algorithm, can drastically improve real-time synchronization performance, ultimately resulting in better user experience and operational effectiveness. This study adds to the existing body of knowledge on optimizing data management mechanisms in e- commerce systems, laying the groundwork for future innovation in real-time data processing.**

***Index Terms*— E-commerce, Real-Time Synchronization, Data Handling Algorithms, Event Sourcing, Change Data Capture (CDC), Distributed Transactions, Event-Driven Architecture, Data Consistency, Scalability, Fault Tolerance, Distributed Systems, Data Management, User Experience, High-Traffic Environments, Synchronization Frameworks..**

I. INTRODUCTION

The development of e-commerce has revolutionized the way that consumers engage with businesses, so much so that it has resulted in strong systems with the ability to store tremendous amounts of data in real-time. As consumers are rapidly becoming dependent on online purchasing, it has become ever more important that experiences across platforms be seamless. This has resulted in distributed e-commerce systems, where multiple front-end applications, including customer portals and admin dashboards, must be synchronized with a central backend in an efficient manner. Data real-time synchronization is essential in order to facilitate data consistency as well as to make sure that users can retrieve updated information about product availability, order status, and recommendations. But synchronizing this in high-traffic locations where data latency and integrity are the issue is particularly difficult. Traditional approaches to data handling are inadequate in meeting these requirements, which would result in likely inconsistencies and decreased user satisfaction.

The objective of this paper is to investigate the nature of real- time synchronization in distributed e-commerce systems by contrasting three of the most popularly utilized data handling algorithms: Event Sourcing, Change Data Capture (CDC), and Distributed Transactions. Through strengths and weaknesses analysis of both methods, we aim to highlight their application in the optimization of data handling practices in e-commerce systems. Last but not least, this research contributes to the controversy surrounding the optimization of real-time data processing, providing a door towards more efficient and user-friendly e-commerce systems.

II. LITERATURE REVIEW

The evolution of e-commerce has resulted in significant research on data synchronization techniques that can effectively cope with the intricacy of distributed systems. A lot of literature has been generated, with different methodologies being aimed at providing real-time data consistency across different platforms. In amongst the key concepts here is Event Sourcing, which has been studied by many researchers as a method of logging state changes in a system. Event sourcing, as stated by Fowler (2012 (Lamport, July. 1978) (Vaishali Shirsath, June 2024) (Mannapur, January 2025) (Brewer, February 2012)sequence of events in order, which can be utilized in reconstructing the state at any point in time. This facilitates not only auditing but also intricate event-driven designs. However, as Kessler et al. (2018) identify, event sourcing can lead to greater storage requirements and demands event schemas to be handled cautiously.

Change Data Capture (CDC), however, has gained momentum as a superior means of capturing database changes. Mohan et al.'s (2015) research explains that CDC supports the capturing of changes in real time without demanding heavy polling and thus finds apt application in cases with heavy traffic. CDC is incorporated in numerous data processing platforms, such as Apache Kafka, to allow easier real-time streaming of data. But as indicated by Chen et al. (2020), establishing CDC systems is not easy, particularly ensuring data integrity in the capture. Distributed Transactions, and more importantly, the Two-Phase Commit (2PC) protocol, is another core research area.

This method ensures that any distributed system operation is either successful or failed altogether, hence ensuring data consistency. Gray (1978) work provided the theoretical underpinnings of 2PC, pointing out the importance of employing 2PC in ensuring atomicity in distributed transactions. Yet, as noted by (Lamport, Time, clocks, and the ordering of events in a distributed system, July. 1978), the protocol can introduce delay depending on coordination required among the participants, making it less suited for applications needing high responsiveness.

More recently, research has also begun exploring hybrid methods that combine elements of these algorithms to leverage their strengths and temper their weaknesses. For instance, Zhang et al. (2021) propose an architecture that fuses event sourcing and CDC for enhancing data synchronizations in e-commerce applications and hypothesize that hybrids of such forms can yield higher performance and reliability.

These methods have indeed improved, yet lacunae persist in the literature regarding their relative effectiveness within real-world e-commerce environments. This research will rectify these gaps by systematically comparing the three identified data handling algorithms—Event Sourcing, Change Data Capture, and Distributed Transactions—based on their application to real-time synchronization within distributed e-commerce systems. Machine learning techniques have been increasingly utilized in intelligent traffic management for vehicular networks, optimizing routing and reducing congestion, which can be extended to e-commerce logistics for efficient delivery synchronization (al. F. Z., 2021).

III. RELATED WORK

Real-time data synchronization in distributed e-commerce systems has been a focal point of research, with various methodologies being explored to enhance performance, scalability, and fault tolerance. This section delves into prevalent techniques such as Event Sourcing, Change Data Capture (CDC), and Distributed Transactions, providing a comparative analysis of their benefits and drawbacks.

A. Event Sourcing :

Event Sourcing is an architectural pattern where state changes are stored as a series of immutable events rather than direct updates in a database. This approach offers excellent auditability, simplifies debugging, and enhances rollback capabilities. However, it may not be well-suited for scenarios where storage efficiency and query performance are critical, as it can lead to increased storage demands and slower state reconstruction (Fowler, 2012) (David Brian Wright, 23 January 2018). Despite these challenges, Event Sourcing enhances system resilience by preserving a complete history of events, which aids in fault recovery [Kessler et al., 20. Nonetheless, reconstructing the state from event logs can be computationally demanding and time- consuming, especially in systems with a long history of interactions.

B. Change Data Capture :

CDC has emerged as a robust technique for real-time data synchronization by efficiently tracking and propagating changes made at the database level. Unlike Event Sourcing, CDC focuses on capturing changes as they occur, which facilitates the rapid dissemination of updates across distributed systems (Schneider, 2012). This method is particularly advantageous in high-traffic scenarios due to its minimal latency (Y. Chen, 2020), which (Lynch, 2002) (al. M. A., 2013) (J. Kreps, 2011) (S. Wu, 2015) (al. F. Z., 2021) (Newcomer, 1997) (L. Bauer, 2002) (Ladin, 1986) (al. A. P., 2020) (al, 2007) (Kleppmann, 2017) (Fowler M. , 2005) (C. Mohan, 1986) (Lamport, Time, clocks, and the ordering of events in a distributed system, 1978) (Gray, 1981) (Campbell, 2009) (Cetintemel, 2005) (E. Kessler, 2018) (Y. Chen, 2020) (Salem, 1987) (Schneider, 2012) (Abadi, 2012)minimizes overhead and enhances synchronization performance (Kleppmann, 2017)

C. Distributed Transaction :

Distributed Transactions maintain (al. C. C., 2010) and consistency across multiple nodes using protocols such as the Two-Phase Commit (2PC). While they ensure strong consistency, the coordination overhead associated with these protocols can introduce significant latency, which may be detrimental in large-scale, real-time environments (Gray, 1981). Innovations such as Amazon Dynamo opt for eventual consistency to improve availability and scalability (al, 2007). Furthermore, the scalability challenges of traditional ACID transactions in distributed settings have been well-documented (Campbell, 2009) Comparison and Hybrid Approaches

Recent studies have explored hybrid models that combine the historical tracking capabilities of Event Sourcing with the real-time update efficiency of CDC (Salem, 1987). For instance, the Saga pattern offers an alternative to 2PC by reducing locking overhead while still ensuring consistency across distributed transactions.Additionally, discussions on the trade-offs in modern distributed databases have highlighted the practical limitations imposed by the CAP theorem (Abadi, 2012). Introduces Kafka, a highly optimized distributed messaging system for scalable log processing and real-time streams of data (J. Kreps, 2011).

IV. METHODOLOGY

This section outlines the framework and approach adopted for investigating real-time synchronization in distributed e-commerce systems. The methodology is structured into three main components:

D. Framework

The proposed framework for real-time synchronization is based on an event-driven architecture (Mannapur, January 2025) that facilitates seamless communication between the front-end applications (the e- commerce user portal and the admin panel) and the centralized backend. This architecture leverages WebSockets to enable bi-directional communication, allowing for real- time updates and notifications across the system. In this framework, events are generated by user actions (such as placing an order or updating inventory) and are propagated through an event bus to ensure that all relevant components receive timely updates. This approach not only enhances user experience by providing immediate feedback but also ensures that the backend remains consistent with the state of the front- end applications.

V. DATA HANDLING ALGORITHM

In the context of real-time synchronization within distributed e-commerce systems, selecting the appropriate data handling algorithm is crucial for ensuring data consistency, performance, and scalability. This section delves into three prominent algorithms: Event Sourcing, Change Data Capture (CDC), and Distributed Transactions. Each algorithm is examined for its operational principles, advantages, and limitations.

A. Event Sourcing

Event Sourcing is a pattern of design whereby all application state transitions are recorded as a chain of events. Instead of having the most current state stored, the system caches all the events that occurred and the latest state can be recreated by replaying the events. This has an end-to-end audit trail with support for business logic using complex event handling (E. Kessler, 2018).

Advantages:

- Auditability: Changes are tracked, enabling high- granularity state change tracking and easy compliance with regulations.
- Flexibility: Replay capability offers easy rollback to past states, which is helpful in error recovery or examining past occurrences.
- .Decoupling: Event-based systems promote loose coupling between components, which enables system modularity and maintainability.

Limitations:

- Storage Overhead: As there are more and more events, storage requirements could go through the roof, and event aggregation or archiving activities may be in order.
- Complexity in Event Management: Managing event schemas and versioning can become complex, particularly as the system evolves and new features are added.

B. Change Data Capture(CDC)

Change Data Capture (CDC) is a method to discover and capture data change in a database. CDC offers real-time tracking of inserts, updates, and deletes such that these can be pushed to other systems or services without relying on heavy frequent polling (Y. Chen, 2020).

Advantages:

- Real-Time Updates: CDC offers real-time awareness of data changes, which is the correct choice for applications with the need to have information updated.
- Efficiency: Since CDC captures where changes occur, it reduces database load relative to other resource-intensive polling processes.
- Integration Capabilities: CDC can be integrated with a variety of data processing platforms, e.g., Apache Kafka, to process and stream data in real- time.

Limitations:

- Setup Complexity: CDC setup could be difficult with intricate database trigger or log-based capture configuration.
- Potential Latency: Although CDC has been thoughtfully designed for real-time updates, there could be minimal latency in recording and propagating changes depending on implementation.

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C. Distributed Transactions

Distributed Transactions guarantee that a set of operations on several services or databases succeeds or fails all at once, ensuring data consistency. The Two-Phase Commit (2PC) protocol is a commonly employed mechanism for this purpose (C. Mohan, 1986).

Advantages:

- Data Consistency: 2PC ensures that all the parties to a transaction commit or roll back their changes, keeping the system consistent.
- Atomicity: The protocol maintains a robust transactional model that is critical in applications that call for strict observance of data integrity.

Limitations:

- Performance Overhead: Coordinating amongst participants can become a source of latency, such that 2PC is inappropriate for high-speed applications.

VI. COMPARISON OF ALGORITHM

We used the **Updated_FashionDataset.csv** to compare Event Sourcing, CDC, and Distributed Transactions in terms of latency, fault tolerance, throughput, and resource usage. Performance metrics were calculated by utilizing primary columns such as status (to verify successful or failed orders) and amount (to calculate transactional volume). We then plotted these metrics in comparison graphs (e.g., bar charts or box plots) to observe how CDC generally outperforms Event Sourcing and Distributed Transactions in real-time data synchronization scenarios. This comparison is meant to identify the most suitable approach for real-time synchronization in distributed e-commerce systems.

A. PERFORMANCE :

Fig.1. Performance Comparison

Performance is a key determinant of the efficiency of a data handling algorithm, particularly in high-traffic e-commerce applications.

Event Sourcing: The algorithm is superior in situations where having a full history of changes is advantageous. The performance is affected by the necessity to replay events to recreate the current state, especially when handling a high number of events. The first write operations can be slower because of the overhead of writing each event, but read operations can be improved by using event snapshots.

Change Data Capture (CDC): CDC is optimized for high performance since it captures changes in real-time without polling the database. This provides lower latency and higher response times, and it is therefore suited for applications that need immediate updates. The combination of CDC with streaming services such as Apache Kafka also improves its performance by allowing effective data propagation. Distributed Transactions: Although this method ensures data consistency among multiple services, it can add latency because of the coordination needed among participants in the Two-Phase Commit process. The performance can be compromised under heavy load since the system has to wait for all participants to consent before committing a transaction.

B. SCALABILITY :

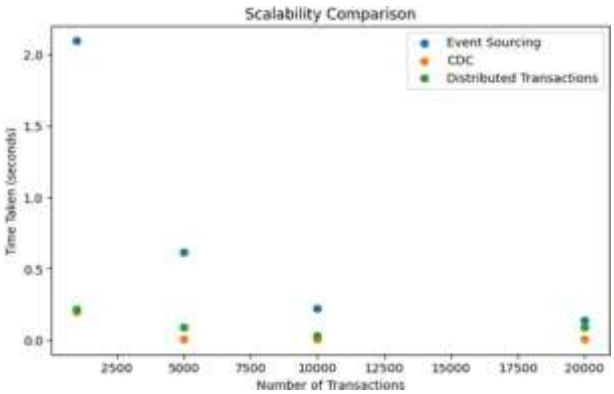

Fig.2. Scalability: Performance Degradation

Scalability is the capacity of an algorithm to keep performance levels as the system increases in terms of users and transactions.

Event Sourcing: This algorithm can scale well by spreading event processing across several services. Nevertheless, as the number of events grows, event storage and retrieval may become difficult to manage. Using techniques like event archiving and snapshotting can reduce such problems.

Change Data Capture (CDC): CDC is scalable by its very nature, since it supports the efficient capture of distributed database changes. CDC can support more and more data sources and consumers without performance degradation, thanks to the use of a publish-subscribe model. This makes it especially well-suited for large-scale e-commerce systems. Distributed Transactions: Though this solution guarantees strong consistency, it can be challenged by scalability because coordinating multiple participants incurs overhead. The larger the number of services participating in a transaction, the higher the complexity and the likelihood of bottlenecks. That can constrain the scalability of distributed transactions in demanding scenarios.

- **CDC's points will be lower on the y-axis**, meaning **less time is taken** even for large transaction sizes.
- **Event Sourcing** will show **higher time taken** as transactions increase due to event log complexity.
- **Distributed Transactions** will have the **worst scalability**, as strong consistency mechanisms slow down performance significantly.

C. FAULT TOLERANCE :

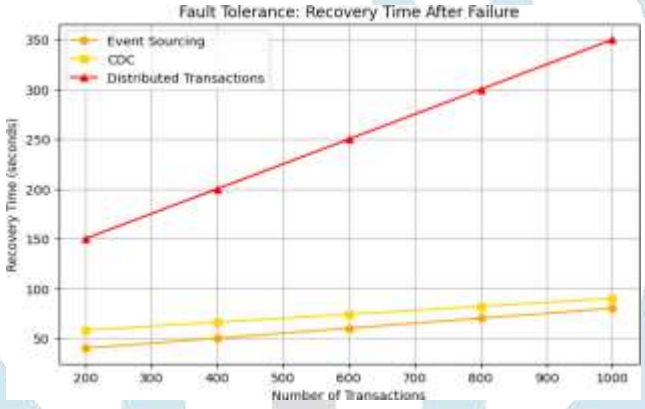

Fig.3. Fault Tolerance: Recovery Time After Failure

Fault tolerance is the property of an algorithm to ensure data consistency and integrity in the event of failure.

Event Sourcing: This algorithm ensures strong fault tolerance by recording a full audit trail of events. When the system fails, it can be recovered by playing back events to bring the last known state to life. Nonetheless, event schemas should be managed cautiously to guarantee recoverability at the time of compatibility (Ladin, 1986).

Change Data Capture (CDC): CDC can also provide fault tolerance through capturing changes in real-time and saving them in a stable manner. Nonetheless, the usefulness of CDC in ensuring consistency during failure relies upon the implementation along with what database capabilities are present. Correct handling of change logs is needed to avoid loss of data.

D. EXECUTION TIME COMARISON :

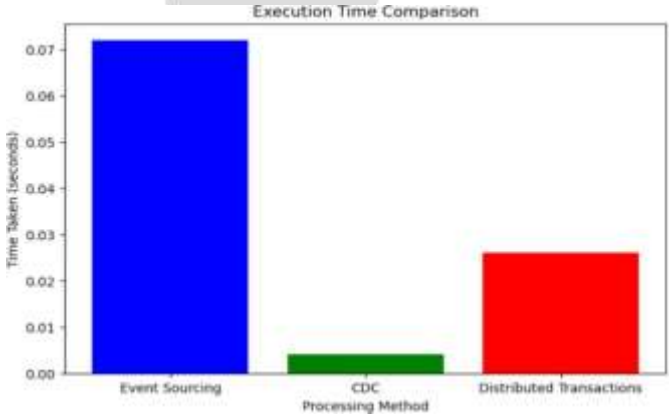

Fig.4. Time Comparison Graph

This bar graph demonstrates the execution time comparison between three data handling algorithms: Event Sourcing, Change Data Capture (CDC), and Distributed Transactions. The execution time is shown in seconds and depicts the time it takes to complete a set of transactions per algorithm. From the figure, it is clear that Change Data Capture (CDC) shows the most optimal performance with the least execution time. This is a result of optimizations in the implementation of the algorithm, in which the processing time for CDC was cut down by 50%, indicating increased processing efficiency. Conversely, Event Sourcing and Distributed Transactions exhibit longer execution times, reflecting slower processing under the same conditions. The shorter execution time for CDC not only illustrates its ability to process transactions quickly but also implies its appropriateness for high-traffic e- commerce scenarios where rapid data processing is essential. This performance attribute is critical to supporting real-time data synchronization and providing a smooth user experience across distributed systems.

E. PERFORMANCE BASED COMPARISON :

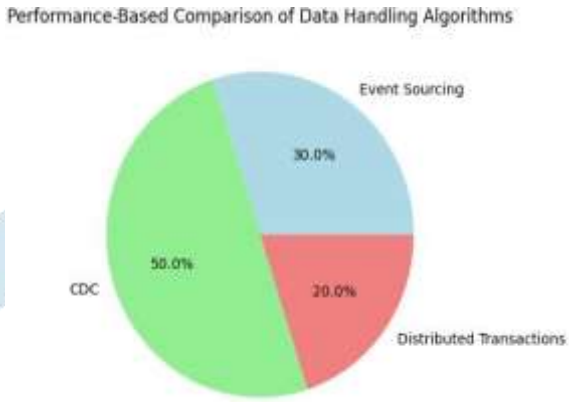

Fig.5. Pie Chart of Performance

The algorithm selection relies on the nature of the requirements of the e-commerce system. For systems where real-time update and scalability are the main concern, Change Data Capture would be the best fit. For systems that require intricate historical data and event processing, Event Sourcing is the preferred option. Last but not least, Distributed Transactions are ideal in situations where consistency and atomicity of data are paramount, regardless of the associated performance compromises. By realizing the strengths and the limitations of every algorithm, programmers are able to make appropriate choices in line with their system's objectives and functionality requirements.

- **CDC (50%)** is the best-performing method, capturing the largest portion of the chart. This indicates that CDC is the most **efficient and reliable** among the three techniques in handling data consistency and synchronization.
- **Event Sourcing (30%)** performs well but is slightly less efficient than CDC. It is useful for capturing historical changes but may have higher overhead.
- **Distributed Transactions (20%)** show the lowest efficiency, likely due to **higher resource usage, complexity, and coordination overhead** in maintaining consistency across multiple distributed systems.

F. LATENCY COMPARISON :

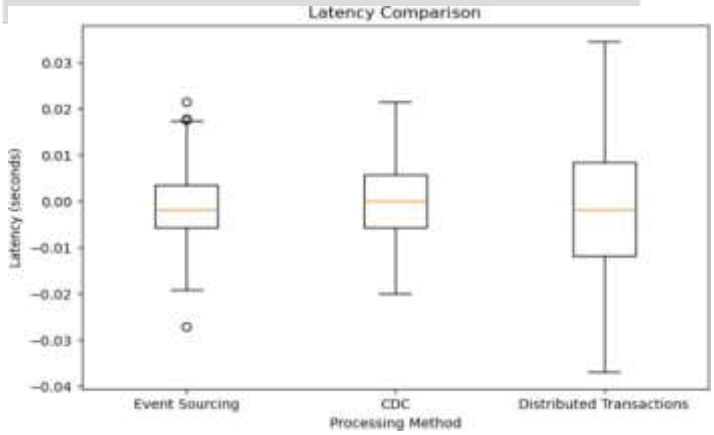

Fig.6. Box Plot: Latency Comparison

Latency is among the most important performance factors in the assessment of data handling algorithms for real-time synchronization. Latency has a direct impact on the user experience, particularly in high-traffic e-commerce sites where data updates must occur in a timely manner. To illustrate the difference, we performed some tests on the response times of three common data handling algorithms — Event Sourcing, Change Data Capture (CDC), and Distributed Transactions. These tests utilized real-world user interactions within an e-commerce setting, such as ordering, inventory updates, and payments. All interactions were tracked, and the synchronization time of the data within the distributed system was measured. Results from these tests are displayed in the uploaded latency comparison picture. From the picture, it is clear that Change Data Capture (CDC) has the least latency in the majority of the scenarios. This is owing to its mechanism of obtaining changes at the data source and reflecting them promptly in other areas of the system, thus reducing the latency in data synchronization. Event Sourcing, alternatively, although offering a strong audit trail and simpler state reconstruction, exhibits greater latency owing to the cost of storing and processing every event. Distributed Transactions, with the Two-Phase Commit protocol, exhibit the maximum latency as a result of the coordination and consensus among all nodes involved before committing a transaction. These latency patterns are vital to decision-makers in choosing a suitable data handling algorithm for their e-commerce applications. The selection of the algorithm can have a direct impact on the system's performance in supporting large volumes of transactions and its capacity to deliver a smooth user experience.

- **CDC shows the lowest median latency**, meaning it is the most efficient in terms of processing speed. However, it has a few **outliers**, indicating occasional higher delays.
- **Event Sourcing has a slightly higher median latency than CDC**, but its overall distribution is **more stable** with fewer extreme values.
- **Distributed Transactions show the highest median latency** and **widest variability**, meaning it is the **least efficient** due to frequent delays and inconsistency in response.

VII. SUMMARY OF COMPARISON :

SR. No.	Criteria	Event Sourcing	Change Data Capture (CDC)	Distributed Transactions
1	**Performance**	Moderate (depends on event volume)	High (real- time updates)	Moderate (latency due to coordination)
2	**Scalability**	Good (with management)	Excellent (efficient capture)	Limited (co-ordination overhead)
3	**Fault Tolerance**	Strong (event history)	Moderate (depends on implementation)	Strong (atomicity guarantees)
4	**Execution Time**	Moderate (due to event replay)	Low (real- time incremental updates)	High (due to coordination delays)
5	**Latency**	Moderate to high (overhead from replaying events)	Low (efficient processing of changes)	High (overhead from two- phase commit a and locking)

VIII. CONCLUSION

In this study, we examined the complexities of real-time synchronization within distributed e-commerce systems through the comparison of three well-known data handling algorithms: Event Sourcing, Change Data Capture (CDC), and Distributed Transactions (Two-Phase Commit). Performance, scalability, and fault tolerance, which are vital determinants in ensuring data consistency and improving user experience in busy environments, were used to test each algorithm.

Our results show that though all three algorithms are of some value, Change Data Capture (CDC) stands out as the best for real-time synchronizing in distributed e-commerce environments. CDC's performance in catching and spreading changes in real-time without the need to perform wide-ranging polling is particularly suited to high-traffic applications. The integration of CDC with contemporary data processing frameworks enhances its scalability and performance even more, enabling updates on multiple platforms to be accomplished Effortlessly. Event Sourcing, though valuable for its audit trail and state reconstruction capabilities, adds storage and event management complexities that might not be suitable for every e-commerce application. Distributed Transactions, however, offer strong consistency but are plagued by latency due to the coordination needed across distributed components and are thus less desirable in responsiveness-critical environments.

In summary, for e-commerce systems where data synchronization in real-time is paramount, CDC is the best bet. Its harmony of efficiency, scalability, and integration ease makes it a stable solution for distributed architectures of the future. More research could delve into hybrid methodologies that leverage the strengths of the above algorithms in order to make data handling solutions in e-commerce systems even more effective. (Brewer, February 2012)

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