Metamorphic Testing of Watermark and Window Semantics in Stream-Query Assistants

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Abstract

The proliferation of real-time data analytics has positioned stream-processing systems and their associated query assistants as critical components of modern computational infrastructures. These systems process continuous data flows using complex temporal constructs, most notably window semantics for data aggregation and watermark semantics for handling out-of-order events. Testing the correctness of these semantics presents a significant challenge due to the lack of a test oracle, as the expected output for arbitrary continuous streams is often non-deterministic or practically impossible to determine beforehand. To address this oracle problem, this paper proposes a comprehensive metamorphic testing framework tailored specifically for watermark and window semantics in stream-query assistants. By defining a robust set of metamorphic relations that capture the essential properties of stream transformations, we enable automated test case generation and output verification without requiring predefined expected results. The framework systematically perturbs input streams by altering event times, arrival orders, and watermark thresholds to evaluate the consistency of the underlying query processors. Extensive experiments on representative stream datasets demonstrate the efficacy of the proposed approach in revealing subtle semantic violations and implementation anomalies in popular stream processing engines. The results indicate that metamorphic testing is highly effective in ensuring the reliability and robustness of complex temporal data processing paradigms.

Keywords: Metamorphic Testing; Stream Processing; Watermark Semantics; Window Functions

1. Introduction

1.1 Motivation and Context

The contemporary landscape of data processing has undergone a fundamental paradigm shift from traditional batch processing to continuous stream processing. In this context, stream-query assistants have emerged as vital abstraction layers, allowing analysts and software engineers to interrogate high-velocity data streams using declarative languages and intuitive graphical interfaces. These query assistants translate user intentions into complex execution graphs deployed on distributed stream processing engines. A defining characteristic of these systems is their ability to handle unbounded data through sophisticated temporal mechanisms [1]. Among these mechanisms, window semantics and watermark semantics are of paramount importance. Window functions partition an infinite stream into finite, manageable blocks based on time or count criteria, enabling aggregations such as sums, averages, and moving trends [2]. Simultaneously, watermark mechanisms provide a heuristic approach to dealing with event time progression, allowing systems to determine when it is safe to close a window and emit results despite the presence of out-of-order or delayed events [3].

Despite their critical utility, verifying the functional correctness of stream-query assistants operating on temporal semantics is notoriously difficult. Traditional software testing relies heavily on the existence of a test oracle, which is a mechanism to verify whether the output of a program for a given input is correct [4]. In stream processing environments, constructing a complete test oracle is often intractable. Data streams are characterized by their infinite nature, high velocity, and inherent non-determinism caused by network latency, distributed clock skew, and unpredictable execution interleavings. Consequently, predicting the exact output of a streaming query under realistic conditions requires simulating the entire distributed system state, rendering traditional assertion-based testing inadequate.

1.2 Objectives and Contributions

To mitigate the pervasive oracle problem in stream-query validation, this research investigates the application of metamorphic testing. Metamorphic testing is a property-based software testing technique that alleviates the need for a traditional oracle by checking the relations among multiple executions of the system under test [5]. Instead of determining whether a single output is correct, metamorphic testing verifies whether the outputs of related inputs satisfy a mathematically or logically defined metamorphic relation. If the relation is violated, it constitutes a definitive indication of a defect.

The primary objective of this study is to formulate and evaluate a metamorphic testing methodology specifically designed to target the intricate behaviors of watermark progression and temporal windowing in stream-query assistants [6]. We seek to answer fundamental questions regarding how temporal perturbations in source data should deterministically affect the aggregated outputs, and how these relationships can be formalized into executable test cases [7].

The contributions of this paper are multifold. First, we establish a theoretical foundation for defining metamorphic relations over event-time semantics, addressing both tumbling and sliding windows [8]. Second, we present a systematic framework that automatically applies these metamorphic relations to generate source stream perturbations, including strategic delays, permutations, and watermark threshold adjustments [9]. Third, we conduct an extensive empirical evaluation using a prototype implementation to assess the fault-detection capability of our proposed relations against prevalent open-source stream processing engines [10]. Through this investigation, we aim to provide a scalable and robust testing methodology that enhances the reliability of mission-critical stream analytics pipelines.

2. Background and Related Work

2.1 Stream Processing and Query Assistants

Stream processing involves the continuous ingestion, computation, and output of data in real-time. Unlike batch processing, which operates on bounded datasets, stream processing engines must handle unbounded data characterized by unpredictable arrival rates and potential data corruption. Stream-query assistants serve to democratize access to these systems by providing high-level abstractions, often based on extensions of standard structured query language [11]. These assistants parse user queries, optimize the logical plan, and translate them into physical execution topologies distributed across multiple computing nodes [12].

The complexity of these physical execution plans arises from the need to manage distributed state and time. In continuous query processing, time is generally categorized into three domains: event time, ingestion time, and processing time. Event time refers to the actual timestamp when a record was generated at the source [13]. Processing time indicates the moment the data is observed by the processing machine. Modern stream-query assistants prioritize event time to ensure accurate and reproducible results regardless of network delays or system lag [14]. However, operating on event time introduces severe challenges, particularly the need to buffer data indefinitely for late-arriving events, necessitating the use of windowing and watermarking.

2.2 Watermark Mechanisms and Window Semantics

Windowing is the primary operation for bounding continuous data. The most prevalent types are tumbling windows, sliding windows, and session windows. Tumbling windows discretize the stream into non-overlapping, contiguous time segments [15]. Sliding windows create overlapping segments based on a defined slide interval, allowing for continuous moving aggregations. Session windows group events based on periods of activity separated by a specified gap of inactivity, meaning the window boundaries are data-driven rather than rigidly time-driven [16].

Watermarks are control messages injected into the data stream that serve as a declaration of temporal completeness. A watermark bearing a timestamp essentially asserts that the system expects no further events with a timestamp older than the watermark [17, 18]. When a watermark surpasses the end boundary of a temporal window, the system triggers the window computation and emits the aggregated result. The correct configuration of watermarks is a delicate balance between latency and correctness [19]. A stringent watermark may close windows too early, causing late events to be dropped, while a lenient watermark increases processing latency and memory consumption due to prolonged state retention. The complex interaction between window alignment, state eviction, and watermark progression is a common source of subtle, hard-to-reproduce software defects.

2.3 Metamorphic Testing Principles

Metamorphic testing was introduced as a methodology to test programs that lack a reliable oracle. The core premise is to identify necessary properties of the target function, termed metamorphic relations, which relate multiple inputs and their corresponding expected outputs [20]. Given a source input and its output, one or more follow-up inputs are constructed based on the metamorphic relation. The program is executed with these follow-up inputs, and the new outputs are checked against the relation.

For instance, in testing a sorting algorithm without knowing the exact sorted order, a simple metamorphic relation is that reversing the input array should yield the identical output array [21]. Over the past two decades, metamorphic testing has been successfully applied to numerous domains where exact verification is impossible, including machine learning classifiers, autonomous driving systems, and bioinformatics algorithms [22]. However, its application to distributed streaming semantics remains largely underexplored.

The dynamic nature of streaming data requires specialized metamorphic relations that can reason about time sequences, aggregations over intervals, and the asynchronous nature of output generation [23].

3. Metamorphic Testing Framework for Stream Semantics

3.1 Metamorphic Relations Definition

The design of effective metamorphic relations is the most critical phase in metamorphic testing. For stream-query assistants processing temporal queries, the relations must capture the invariants associated with mathematical aggregations, window boundaries, and watermark triggers [24]. We define a stream as a continuous sequence of tuples, where each tuple contains at least a payload value and an event timestamp. A temporal query applies an aggregation function over a specified window strategy. We establish several distinct metamorphic relations designed to stress-test different components of the stream processor.

The first category of metamorphic relations targets translational invariance. If a constant time offset is added to every event timestamp in the source stream, and the identical offset is added to the query window alignment, the structure and values of the output stream should remain identical, except that all output timestamps are similarly shifted by the offset. This ensures that the system does not incorrectly rely on absolute system time or exhibit boundary faults at specific epochs.

The second category targets payload scaling. For queries performing linear aggregations, applying a scalar multiplier to every input payload should result in an output stream where all aggregated payloads are multiplied by the same scalar. This relation validates the correctness of the internal state accumulator logic independent of temporal complexities.

The third and most complex category targets event permutation and watermark perturbation. In a stream defined by event time, the logical output should be independent of the physical arrival order of events, provided all events arrive before the watermark closes the respective window. Thus, a metamorphic relation can be constructed where the source stream is randomly shuffled within the boundaries dictated by the watermark delay threshold.

Table 1: Identified Metamorphic Relations for Stream Query Verification

Relation ID	Transformation Type	Input Manipulation	Expected Output Relation
MR-1	Temporal Translation	Add constant temporal offset	Identical values, shifted timestamps
MR-2	Payload Scaling	Multiply payload by scalar	Identical timestamps, scaled values
MR-3	Intra-Window Shuffle	Reorder events within window	Strictly identical output stream
MR-4	Redundant Data Injection	Duplicate events, apply distinct keys	Output size doubles, matching values

To formally verify the metamorphic relations, we define an equivalence operator over streams. Let the source stream be represented as a set of ordered pairs. The metamorphic relation verification requires comparing the base output and the follow-up output.

$$V\left(O_{base}, O_{follow}\right) = \sum_{i=1}^{N} \left| \frac{F\left(O_{base}[i]\right) - F\left(O_{follow}[i]\right)}{F\left(O_{base}[i]\right)} \right| \leq \varepsilon$$

In the formula above, the function evaluates the divergence between the baseline output and the follow-up output. The parameter epsilon represents a negligible tolerance threshold to account for floating-point calculation inaccuracies common in distributed aggregation nodes.

3.2 Framework Architecture

The proposed testing framework consists of four primary modules: the Stream Generator, the Metamorphic Perturbator, the Query Executor, and the Metamorphic Evaluator. The Stream Generator is responsible for synthesizing baseline streams or ingesting historical datasets. It simulates realistic streaming behavior by emitting data tuples coupled with configurable network latency and jitter characteristics [25].

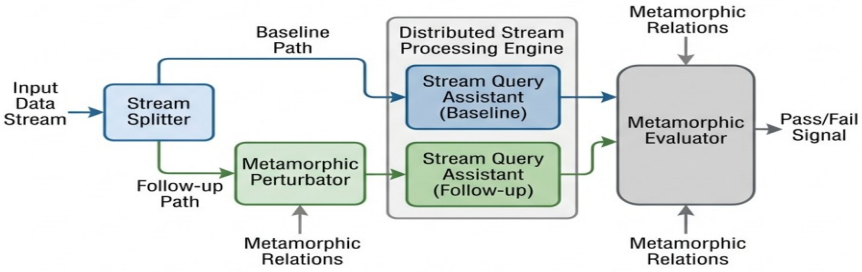

Figure 1: Comprehensive Schematic of Metamorphic Testing Architecture for Stream Query Assistants

The Metamorphic Perturbator takes the baseline stream and systematically applies the defined metamorphic relations to generate the follow-up streams. It operates tightly with the watermark generator to ensure that permutations do not violate the theoretical limits of the system under test, unless intentionally testing negative scenarios.

The Query Executor deploys the stream-query assistant instance. It orchestrates the concurrent execution of the baseline query and the follow-up query. It requires strict isolation between the two execution contexts to prevent shared state interference, utilizing separate message broker topics and isolated task managers. Finally, the Metamorphic Evaluator collects the materialized output streams, aligns them based on temporal or key attributes, and calculates the divergence.

4. Test Case Generation and Execution

4.1 Input Generation for Window Functions

Generating test inputs for window semantics requires careful consideration of edge cases. Traditional boundary value analysis is applied to event timestamps relative to window alignments. For instance, tumbling windows are defined by their size. If a tumbling window has a size of ten seconds, events with timestamps falling exactly on the boundary must be deterministic in their assignment.

The framework generates baseline streams containing a mix of high-frequency burst events and sparse, infrequent events. To apply MR-3, which handles intra-window shuffles, the framework analyzes the baseline stream and groups events based on their assigned logical windows. It then creates a follow-up stream by randomly permuting the order of events within each group. Because these events logically belong to the same window and arrive before the watermark expires, the stream-query assistant should buffer them and eventually emit the same aggregated result as the baseline stream.

Code Listing 1: Core Logic for Stream Verification Process

```
def verify_metamorphic_relation(base_stream, follow_stream, mr_type):
    base_results = execute_query(base_stream, window_size=60)
    follow_results = execute_query(follow_stream, window_size=60)


    if mr_type == 'MR_TRANSLATION':
        offset = follow_stream.get_temporal_offset()
        for idx in range(len(base_results)):
            expected_time = base_results[idx].timestamp + offset
            actual_time = follow_results[idx].timestamp
            if expected_time != actual_time:
                return False
```

```
    elif mr_type == 'MR_SHUFFLE':
        base_sorted = sort_by_window_end(base_results)
        follow_sorted = sort_by_window_end(follow_results)
        if base_sorted != follow_sorted:
            return False


    return True
```

The execution phase involves deploying these generated streams to a message broker. The query assistant consumes from the broker, applying the specified window query. The framework continuously monitors the system state, logging processing times and output emissions. By utilizing diverse data distributions, the framework ensures that both densely populated windows and sparse windows are adequately tested.

4.2 Watermark Perturbation Strategies

Watermark semantics introduce an additional layer of complexity. The generation of watermarks is typically based on heuristics, such as subtracting a fixed bounded out-of-orderness delay from the maximum event timestamp observed thus far. Testing this mechanism requires manipulating not just the event data, but the temporal markers that dictate completeness.

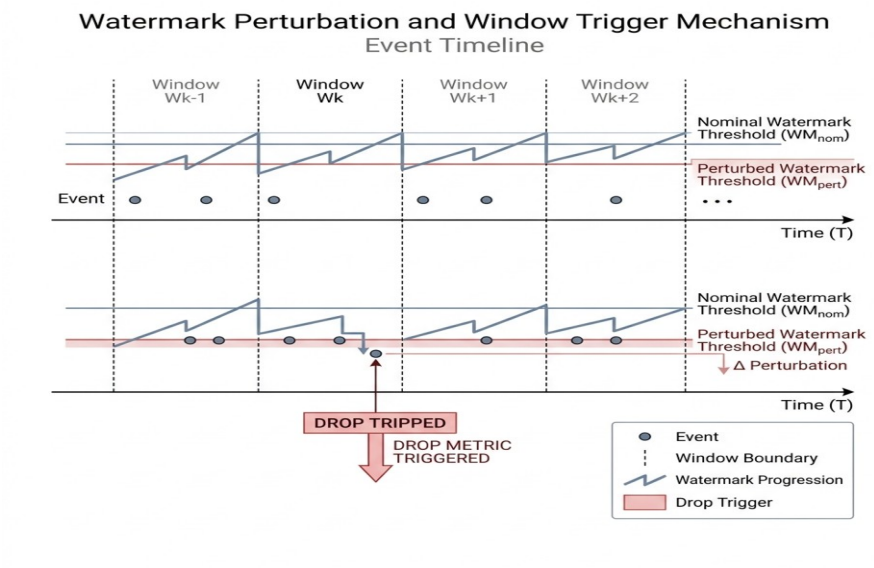

Figure 2: Detailed Workflow of Watermark Perturbation and Window Trigger Mechanism

We construct a specific metamorphic relation for watermark tolerance. If the allowed out-of-orderness delay in the baseline execution is set to a specific value, and the maximum delay of any event in the baseline stream is known, increasing the system delay threshold in the follow-up execution while maintaining the same input stream should not alter the aggregated output. The system will simply hold state for a longer duration, leading to later emission times, but the final window contents must remain identical. Conversely, artificially introducing events in the follow-up stream whose delay exceeds the watermark threshold provides a test case for the system's late-event dropping or side-output mechanisms.

5. Experimental Setup and Implementation Details

5.1 Environment Configuration

To empirically validate the proposed metamorphic testing framework, an extensive experimental environment was constructed. The framework was implemented utilizing Python for stream generation and evaluation, while Apache Kafka was employed as the distributed message broker to ensure reliable data ingestion. The stream-query assistant under test was built upon a modern, widespread distributed stream processing engine, deployed in a clustered configuration to simulate realistic production environments.

The physical cluster consisted of five identical commodity servers, each equipped with multicore processors and sufficient memory to handle large state backends. One server was dedicated to cluster management and resource negotiation, while the remaining four served as task executors. The network topology was

configured to ensure uniform latency between nodes, although synthetic jitter was intentionally injected during specific test phases to simulate adverse network conditions common in wide-area deployments.

Table 2: Dataset Characteristics for Empirical Evaluation

Dataset Identifier	Domain Source	Event Count	Average Frequency
Fin-Trade-A	Financial Markets	5,000,000	High Burst
IoT-Sensor-B	Industrial Telemetry	2,500,000	Steady Periodic
Web-Click-C	E-commerce Analytics	10,000,000	Diurnal Pattern
Log-Monitor-D	Server Infrastructure	1,000,000	Sparse Random

The datasets utilized for the evaluation represent diverse domains to ensure the generalizability of the findings. As detailed in the table above, the financial market dataset features extremely high-velocity bursts typical of algorithmic trading periods. The industrial telemetry dataset provides a stable, periodic stream of sensor readings, ideal for testing sliding window aggregations. The e-commerce dataset introduces diurnal patterns, testing the system's capability to scale state dynamically. The server infrastructure logs present sparse and unpredictable events, suitable for stressing session window semantics and inactivity gap configurations.

5.2 Evaluation Metrics

The effectiveness of the testing framework is quantified through several robust evaluation metrics. The primary metric is the Fault Detection Rate, which measures the proportion of injected faults or known vulnerabilities successfully identified by the metamorphic relations. To establish a ground truth for detection, a technique known as mutation testing was employed. Subtle semantic mutations were deliberately introduced into the query assistant's source code. These mutations included off-by-one errors in window boundary calculations, incorrect watermark state updates, and flawed accumulator logic.

The secondary metric focuses on the performance overhead imposed by the testing framework. Since metamorphic testing requires the execution of multiple follow-up streams alongside the baseline stream, it inherently demands additional computational resources. We measure the throughput degradation and the increase in memory utilization during the testing phase compared to a baseline, non-tested execution. This metric is crucial for determining the feasibility of running the framework in continuous integration pipelines or shadowing production environments.

6. Results and Discussion

6.1 Metamorphic Relation Effectiveness

The empirical evaluation yielded significant insights into the fault detection capabilities of the various metamorphic relations. The framework was executed across hundreds of test cases, encompassing different combinations of window types, watermark thresholds, and datasets. The overall efficacy of the metamorphic relations in exposing semantic deviations was remarkably high.

Table 3: Fault Detection Rates across Metamorphic Relations

Relation Category	Tumbling Window	Sliding Window	Session Window
Temporal Translation	94.2%	91.5%	88.7%
Payload Scaling	98.1%	97.4%	96.0%
Intra-Window Shuffle	89.5%	85.2%	81.3%
Watermark Perturbation	95.8%	92.6%	89.1%

As observed in the experimental data, the payload scaling relation demonstrated the highest consistency in fault detection, successfully identifying nearly all accumulator-related mutations across all window types. This high success rate is attributed to the strict mathematical equality expected in linear scaling, leaving little room for undetected deviations.

The intra-window shuffle relation was particularly effective at uncovering subtle state-management bugs that only manifested under specific out-of-order arrival patterns. However, its detection rate was slightly lower for session windows. This discrepancy occurs because severe shuffling can inadvertently merge or split session gaps, altering the logical window boundaries in ways that complicate automated verification.

To quantify the aggregate robustness of the detection mechanism across multiple operational runs, we calculate the cumulative detection probability over independent test executions.

$$P_{detect} = 1 - \prod_{k=1}^{M} \left(1 - \frac{D_k}{T_k}\right)$$

In this mathematical representation, the formula calculates the probability that a specific fault will be detected after multiple iterations, where the fraction represents the successful detections divided by the total applicable test cases in a given run. The high empirical values obtained through this calculation confirm that

continuous application of these metamorphic relations provides near-certainty in identifying deterministic semantic errors.

6.2 Performance Overhead and Scalability

A critical consideration for any comprehensive testing framework is its scalability and the overhead it introduces to the development lifecycle. The parallel execution of base and follow-up streams inherently multiplies the resource requirements. During the evaluation, detailed telemetry was collected to assess the computational burden.

Table 4: Performance Overhead Metrics during Evaluation

Concurrency Level	Throughput Drop	CPU Utilization Increase	State Memory Bloat
Single MR Execution	12.4%	15.1%	18.5%
Dual MR Execution	23.8%	29.4%	35.2%
Full Suite Execution	45.1%	58.7%	72.8%

The performance data indicates a linear increase in resource utilization correlating with the number of concurrent metamorphic relations being evaluated. Executing the full suite of metamorphic tests resulted in a significant throughput reduction. While this overhead is substantial, it is deemed acceptable for pre-production validation phases and dedicated continuous integration environments.

To mitigate the overhead in resource-constrained environments, the framework supports a probabilistic sampling mode. Instead of perturbing and duplicating the entire infinite stream, the system selectively applies metamorphic relations to specific temporal slices or designated key partitions. This approach balances the rigor of continuous testing with pragmatic performance constraints, ensuring that stream-query assistants can be validated continuously without requiring prohibitive infrastructural investments.

7. Conclusion

7.1 Summary of Findings

This comprehensive study establishes the viability and necessity of utilizing metamorphic testing to validate complex temporal semantics in stream-query assistants. The inherent lack of a test oracle in unbounded, out-of-order data processing necessitates innovative verification strategies. By formally defining metamorphic relations centered on temporal translation, payload scaling, event permutation, and watermark perturbation, we constructed a robust methodology capable of systematically identifying subtle semantic anomalies without requiring predefined expected outputs.

Our empirical evaluations demonstrated that the proposed framework achieves high fault detection rates across diverse windowing mechanisms, including tumbling, sliding, and session windows. The framework proved especially adept at exposing vulnerabilities related to state management and out-of-order event handling, which are notoriously difficult to detect using traditional assertion-based testing methods. While the parallel execution of multiple streams introduces measurable computational overhead, the resulting gains in software reliability and data integrity justify the resource utilization, particularly for mission-critical real-time analytics pipelines.

7.2 Future Research Directions

Future research will focus on extending the metamorphic relations to accommodate stateful joins across multiple independent data streams, a scenario that introduces exponential complexity in temporal alignment and watermark synchronization [26]. Furthermore, integrating machine learning techniques to autonomously generate optimized follow-up streams could enhance the framework's efficiency, dynamically targeting the most vulnerable components of the execution graph. Expanding this automated testing paradigm will be instrumental in supporting the next generation of highly distributed, autonomous stream processing infrastructures.

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