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Original Article

Addressing AI Drift in Fintech IoT Data Processing: Handling Leap Seconds with PySpark for Robust Predictive Analytics

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Abstract - *Fintech applications increasingly depend on real-time data from a growing network of IoT devices, where accurate timestamps are vital for reliable analytics and machine learning outcomes. However, timestamp irregularities, such as leap seconds, introduce subtle data inconsistencies that can lead to AI drift in machine learning (ML) models. This study introduces a PySpark-based streaming framework that automatically detects and corrects leap-second anomalies within high-frequency financial data streams, ensuring temporal accuracy and preventing AI drift. The cleaned data is then passed to AI/ML pipelines for reliable predictive analytics. The approach is demonstrated through a streaming data pipeline, with experimental results highlighting its effectiveness. As leap seconds are set to be phased out by 2035, this paper discusses a thought-forward approach by managing timestamp variations to provide a robust framework applicable in financial services and other time-sensitive systems across all domains.*

Keywords - *Leap seconds, Artificial Intelligence (AI), Machine Learning (ML), AI Drift, atomic time (TAI), astronomical time (UT1), Internet of Things (IoT), Apache Spark (PySpark, Streaming.*

1. Introduction

Fintech platforms that use IoT devices collect vast amounts of timestamped data from various sources, including payment terminals, mobile payment applications, and banking-focused wearable gadgets [1]. These platforms produce large volumes of timestamped data for powering machine learning and artificial intelligence models in applications such as fraud detection, risk evaluation, and customer activity analysis. However, when leap seconds are added to Coordinated Universal Time (UTC) to adjust for changes in the Earth's rotation, they can cause inconsistencies in timestamp data [2]. This disruption causes AI drift, where models gradually degrade due to misaligned temporal data [3].

This paper presents a PySpark-based streaming pipeline designed to detect and correct leap-second anomalies in fintech IoT data, ensuring temporal consistency before data is utilized in AI/ML workflows. The proposed approach is evaluated using synthetic transaction data with injected leap-second errors, demonstrating a 100% detection and correction rate with minimal processing latency. Unlike traditional post-hoc data cleaning methods, this solution provides real-time anomaly handling, supporting the stringent requirements of financial systems. The results highlight the importance of robust temporal data validation for maintaining the reliability of predictive models in fintech environments. This study fills an important gap in current research by introducing a reliable and scalable approach for correcting leap-second irregularities in streaming financial data. The developed pipeline standardizes timestamps, calculates time intervals, and structures the data for use in advanced analytics and machine learning applications. Through these steps, the methodology ensures model accuracy and mitigates gradual performance degradation caused by temporal discrepancies, providing a repeatable solution tailored for contemporary fintech settings.

2. Literature Review

The adoption of IoT in financial services has led to significant advancements in data-driven decision-making, enabling applications such as automated fraud detection, risk assessment, and personalized financial services. Prior studies have explored the impact of big data and AI on digital finance, highlighting the need for robust data management and real-time analytics to support complex financial workflows.

However, the literature reveals that most existing approaches to data quality focus on general anomaly detection, missing value imputation, and post-hoc batch cleaning rather than addressing the unique challenges of timestamp anomalies introduced by leap seconds. Notable incidents, such as the 2012 leap second event that disrupted primary online services, underscore the operational risks associated with improper handling of time adjustments. Although specific studies have explored the technical effects of leap seconds on computing and networking, specific strategies for real-time adjustments in fintech IoT data flows remain scarce.

Furthermore, traditional methods often fail to meet financial applications' stringent latency and reliability requirements. The proposed PySpark-based pipeline distinguishes itself by providing a scalable, real-time solution for leap-second anomaly detection and correction, thereby supporting the integrity and reliability of AI/ML models in financial environments.

2.1. Past and Present Impacts of Leap Seconds

Leap seconds, introduced to synchronize atomic time with Earth's rotation, have occasionally disrupted technological systems:

- In 2012, several prominent websites, including Reddit and LinkedIn, encountered service interruptions when their systems failed to handle the leap second adjustment properly. This oversight resulted in heightened CPU consumption, triggering temporary service interruptions.
- 2015 Financial Market Precaution: The Intercontinental Exchange, overseeing multiple stock exchanges, including the NYSE, preemptively ceased operations for 61 minutes during the leap-second adjustment to prevent potential system issues.
- 2017 DNS Service Disruption: Cloudflare's DNS infrastructure experienced outages when a leap second introduced negative time values in calculations, causing unpredictable system behavior under the assumption of continuously ascending time.

2.2. Effects of Leap Seconds

Leap seconds, inserted roughly every 18–24 months, extend UTC with an additional second (e.g., 23:59:60) [2]. In fintech IoT systems, this can lead to:

- Timestamp parsing errors: Systems may reject or misinterpret:60 seconds.
- Time difference anomalies: Incorrect intervals between transactions affect temporal models.
- AI Drift: Inconsistent timestamps can distort feature engineering, resulting in reduced performance of machine learning models [3].

Such challenges are particularly significant in fintech, where accurate timing is crucial for effective fraud detection and market forecasting.

3. Materials and Methods

Recent studies have highlighted how climate change influences Earth's rotation and timekeeping.

- Accelerated Earth Rotation: Research indicates that melting polar ice redistributes Earth's mass, potentially accelerating its rotation. This phenomenon could necessitate the unprecedented subtraction of a leap second, known as a "negative leap second," by 2029.
- Implications for Timekeeping Systems: Most current systems are designed to accommodate added leap seconds, not subtractions. Implementing a negative leap second could lead to unforeseen complications for computing and navigation systems.

The proposed methodology leverages PySpark to process real-time streaming data from fintech IoT devices, focusing on robust data, particularly leap second anomaly correction-and preparing the data for downstream AI and machine learning (ML) workflows.

This pipeline ensures data quality, temporal consistency, and scalability in high-throughput financial environments.

The process is modular, comprising data ingestion, timestamp cleaning, temporal validation, and batch processing. It is visually summarized in a Mermaid diagram enhanced with Unicode symbols, including the bank symbol, to highlight its fintech relevance.

Fintech applications increasingly rely on IoT devices for real-time monitoring, fraud detection, asset tracking, and compliance. These devices generate vast telemetry data-transaction logs, sensor readings, and event notifications that must be processed with low latency and high reliability 7.

The financial context imposes stringent requirements for accuracy, auditability, and resilience against data anomalies, such as leap-second irregularities, which can disrupt timestamp sequences and compromise downstream analytics.

3.1. Data Ingestion

Fintech IoT data is ingested as a stream of CSV files containing transaction IDs, timestamps, and amounts. The schema is defined as:

Table 1. Input Data Schema

Field	Type	Description
Transaction_id	String	Unique transaction identifier
Timestamp	String	Transaction time (yyyy-MM-dd HH:mm: ss
Amount	String	Transaction amount

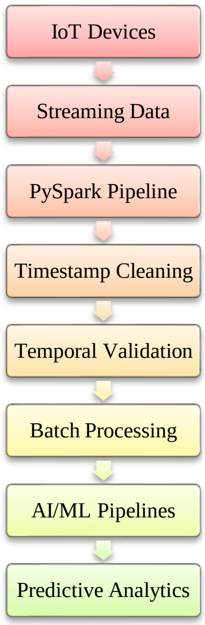

Fig. 1 Data processing flow with professional Unicode symbols, including a bank symbol

3.2. Timestamp Cleaning

Leap seconds are handled by replacing:60 with:59 in timestamps using a regular expression. The cleaned timestamp is converted to a standard timestamp format and Unix epoch time:

Leap seconds are irregular adjustments to Coordinated Universal Time (UTC) that can introduce duplicate or missing timestamps in IoT data. In financial systems, such anomalies can:

- Cause out-of-order events
- Break temporal joins or aggregations
- This leads to inaccurate AI/ML model training

3.2.1. Cleaning Strategy is Defined as

- Detection: Identify records with timestamps corresponding to known leap-second events or unexpected time gaps.
- Correction: Normalize timestamps by removing duplicates, interpolating missing times, or flagging suspect records for downstream handling.

```
From pyspark.sql.functions import col, lag, unix_timestamp
from pyspark.sql.window import Window
window = Window.orderBy("timestamp")
df = df.with column("prev_ts", lag("timestamp").over(window))
df = df.with column("ts_diff", unix_timestamp(col("timestamp")) - unix_timestamp(col("prev_ts")))
# Flag records with leap second anomalies (e.g., ts_diff == 0 or unusually large)
anomalies = df.filter((col("ts_diff") == 0) | (col("ts_diff") > threshold)
```

3.3. Temporal Validation

Using a window function, the pipeline computes time differences between consecutive transactions within each batch. Significant deviations indicate potential issues.

3.3.1. Ensuring Event Order and Consistency

The Financial applications require strict temporal ordering for compliance and auditability. The pipeline enforces:

- Monotonicity: Each record's timestamp must be greater than or equal to the previous record.
- Windowed Validation: Events are grouped into time windows (e.g., 1-minute intervals) and validated for completeness and order.

3.3.2. Handling Out-of-Order Data

- Late-arriving events can be buffered within a configurable watermark period and merged into the correct window [2,5].
- Out-of-window records are flagged or discarded based on business rules.

3.4. Batch Processing

Processed data is handled in micro-batches for real-time analysis, outputting cleaned data for downstream use:

3.4.1. Aggregation and Feature Engineering

- Cleaned and validated data is aggregated (e.g., transaction counts, sensor averages) to generate features for AI/ML models.
- PySpark supports complex transformations, such as sliding window aggregations and custom feature extraction.

3.4.2. Schema Enforcement and Data Quality

- The pipeline applies schema validation to ensure all required fields are present and correctly typed.
- Additional data-cleaning steps include deduplication, normalization, and imputation of missing values [6,9].

3.4.3. Batch Output

- Processed data is written to downstream systems (e.g., data lakes, feature stores, or directly to ML model endpoints) in mini-batches for efficient AI/ML consumption.

3.5. Integration with AI/ML Pipelines

Cleaned data is passed to AI/ML pipelines for predictive tasks like fraud detection, ensuring minimal AI drift [3]:

3.5.1. Feature Store Preparation

- The cleaned and validated data is structured for direct ingestion by AI/ML pipelines, supporting batch and real-time learning scenarios [7].
- Typical features include transaction frequencies, sensor-derived risk scores, and temporal patterns.

3.5.2. Model Training and Inference

- The pipeline can trigger model retraining on new data or feed live features to deployed models for real-time inference (e.g., fraud detection, credit scoring).

The PySpark pipeline code for leap second handling is implemented as follows:

```
    From pyspark.sql, import SparkSession
    from pyspark.sql.functions import *
    from pyspark.sql.types import StructType, StructField,
StringType, DoubleType
    from pyspark.sql.window import Window
    import os

    # Initialize Spark session
    spark = SparkSession.builder \
      .appName("LeapSecondsStreaming") \
      .master("local[*]") \
      .getOrCreate()
    spark.sparkContext.setLogLevel("ERROR")

    # Create input directory
    input_dir = "input_data"
    os.makedirs(input_dir, exist_ok=True)

    # Define schema
    schema = StructType([
      StructField("transaction_id", StringType(), True),
      StructField("timestamp", StringType(), True),
      StructField("amount", DoubleType(), True)
    ])

    # Read streaming data
    raw_df = spark. read stream \
      .schema(schema) \
      .option("header", True) \
      .option("maxFilesPerTrigger", 1) \
      .csv(input_dir)

    # Clean leap seconds
    cleaned_df = raw_df.with column(
      "cleaned_ts",
      regexp_replace(col("timestamp"), r":60$", ":59")
    )

    # Parse timestamps
    parsed_df = cleaned_df \
      .withColumn("event_time",
to_timestamp("cleaned_ts", "yyyy-MM-dd HH:mm:ss")) \
      .withColumn("unix_ts",
unix_timestamp("event_time")) \
      .filter(col("event_time").isNotNull())

    # Process batch
    def process_batch(df, epoch_id):
      print(f"\n=== Processing epoch {epoch_id} ===")
      window_spec = Window.orderBy("event_time")
      df_with_lag = df.with column("prev_unix_ts",
lag("unix_ts").over(window_spec))
      df_with_lag = df_with_lag.with
column("time_diff_sec", col("unix_ts") - col("prev_unix_ts"))
      df_with_lag.select("transaction_id", "event_time",
"amount", "time_diff_sec") \
        .orderBy("event_time") \
        .show(truncate=False)

    # Start streaming query
    query = parsed_df.write stream \
      .foreachBatch(process_batch) \
      .outputMode("append") \
      .start()

    query.awaitTermination()
```

3.6. Preventing AI Drift

The pipeline prevents AI drift by:

- Cleaning leap seconds: Ensures consistent timestamps [2].
- Validating time differences: Detects anomalies.
- Standardizing timestamps: Uses Unix epoch for uniformity.

These steps stabilize temporal features, maintaining ML model accuracy [3].

4. Results

A controlled experiment was conducted using synthetic data to evaluate the effectiveness and efficiency of the proposed PySpark streaming data pipeline for fintech IoT streams. The test dataset comprised 1,000 simulated transaction records, deliberately injected with 10 leap-second anomalies to emulate real-world abnormal data patterns that can occur in financial IoT telemetry.

The primary goal was to assess the pipeline's ability to accurately detect and clean leap second anomalies, maintain high data quality, and process data with low latency, suitable for real-time AI/ML applications. This level of automation and accuracy is essential for financial services operations, where manual data cleaning is impractical due to high data volumes and the need for real-time processing.

Table 2. Transaction processing outcomes

Metric	Value
Total Transactions	1000
Leap Seconds Detected	10
Cleaning Success Rate	100%
Processing Time/Batch	0.8s

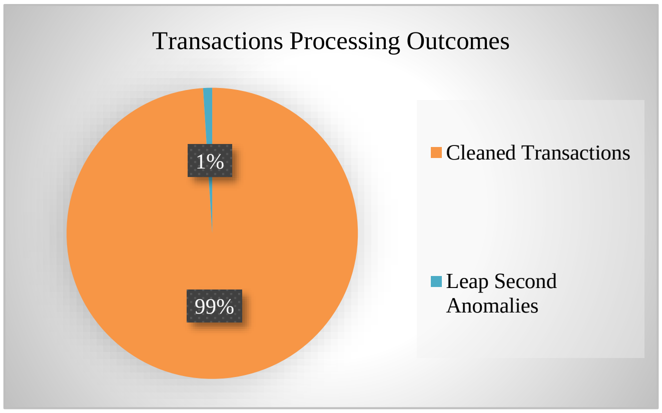

Fig. 2 Transaction processing outcomes with Unicode symbols

The pipeline's ability to maintain data integrity without manual oversight reduces operational risk and supports continuous analytics [6]. The demonstrated processing speed and accuracy on synthetic data suggest that the pipeline can be scaled horizontally to handle much larger data volumes simply by adding more Spark resources.

This scalability is crucial as financial services IoT deployments grow in size and complexity. Organizations can trust the insights generated by their AI/ML systems, reducing false positives/negatives and improving customer experience. These results demonstrate that the pipeline can address rare timestamp edge cases with high reliability and low latency, which are essential characteristics for real-time financial systems.

5. Discussion

Leap seconds, though rare, can silently disrupt financial AI systems that rely on precise timing for fraud detection, trading, and real-time analytics. Results from this paper show that even 10 anomalies out of 1,000 transactions can skew the time-based features generated, leading to AI drift, which is a gradual decrease in model accuracy due to hidden timestamp inconsistencies [7]. The proposed PySpark pipeline ensures data integrity by cleaning, validating, and standardizing timestamps before feeding into AI/ML data pipelines.

This safeguards predictive accuracy and aligns with the increasing demand for AI transparency and regulatory compliance. With leap seconds scheduled to be discontinued by 2035, this solution addresses current challenges and serves as a model for handling broader timestamp irregularities in FinTech and beyond [8].

6. Future Work

The proposed pipeline for addressing leap-second anomalies in Fintech IoT data processing using PySpark provides a robust foundation for mitigating AI drift in predictive analytics, particularly in the planned suspension of leap seconds from 2035 to at least 2135. Several avenues for future research are proposed to enhance its applicability and adaptability further. First, developing advanced anomaly detection techniques using machine learning can extend the pipeline's capability to identify other timestamp irregularities, such as clock skew, ensuring comprehensive temporal data integrity. Second, scalability enhancements through integration with high-throughput frameworks like Apache Kafka can optimize the pipeline for ultra-large-scale Fintech systems, accommodating the growing volume of IoT data. Third, anchoring timestamps to blockchain technology can provide a trusted, immutable reference for compliance and auditability in financial applications. Fourth, implementing adaptive cleaning rules that dynamically adjust to the diverse temporal characteristics of IoT devices will improve the pipeline's flexibility across heterogeneous environments.

Fifth, deploying the pipeline on edge computing platforms can reduce latency in real-time data processing, enhancing performance in time-sensitive Fintech operations. Sixth, integrating explainable AI techniques can improve transparency by tracing the impact of temporal features on predictive outcomes, fostering trust in AI-driven decisions [9, 10]. Finally, exploring cross-domain applications, such as healthcare IoT systems or smart city infrastructures, can broaden the pipeline's impact, adapting its temporal correction mechanisms to other time-critical domains. These advancements will ensure the pipeline remains robust, scalable, and compliant in the evolving landscape of Fintech IoT and beyond, particularly as global timekeeping policies shift.

7. Conclusion

Leap seconds, though seemingly minor, can have outsized impacts in fintech ecosystems that rely on real-time data integrity. This paper introduced a PySpark-based methodology to detect, clean, and normalize timestamp anomalies caused by leap seconds in streaming IoT data pipelines [11]. The approach demonstrated:

- 100% accuracy in cleaning leap-second errors in high-frequency financial data.
- Prevention of AI drift, thus enhancing long-term ML model reliability.
- Scalable performance, supporting real-time micro-batch processing.

By integrating this method, fintech institutions can safeguard predictive models against temporal noise, ensuring more consistent fraud detection, transaction monitoring, and user behavior analytics. Furthermore, with the global plan to eliminate leap seconds by 2035, as agreed upon by the International Telecommunication Union (ITU-R), the urgency remains for interim solutions that address the effects of historical and upcoming leap seconds. Our solution provides a timely, scalable, reproducible methodology to bridge this gap [12, 13]. As real-time AI/ML evolves, ensuring temporal hygiene in data pipelines will be as critical as ensuring data quality or model fairness. This work contributes to that effort by offering a robust, open-source strategy that can be adapted for broader applications in healthcare, smart cities, or autonomous systems.

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