МЕДИЦИНА, ПЕДАГОГИКА И ТЕХНОЛОГИЯ: ТЕОРИЯ И ПРАКТИКА
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SCALABLE ALGORITHMS FOR HIGH-FREQUENCY TRADING DATA ANALYSIS: FROM TRADITIONAL INDEXING TO MODERN STREAM PROCESSING

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Abstract

High-frequency trading (HFT) systems generate and process vast volumes of financial data in real time, demanding scalable and efficient algorithms for data analysis. This study presents a comparative investigation of classical indexing techniques and modern stream processing algorithms for HFT data analysis. We examine the limitations of traditional database indexing (e.g., B-trees, hash indexes) in the context of low-latency, high-throughput environments and contrast them with contemporary stream processing frameworks and probabilistic data structures. Using synthetic and real-world trading datasets, we implement and benchmark representative algorithms in Python and SQL, evaluating their performance in terms of latency, throughput, and scalability. Our results demonstrate that while classical methods remain effective for batch analytics and historical queries, modern stream processing approaches-such as windowed aggregation, approximate counting, and event-driven architectures-offer significant advantages for real-time HFT applications. The findings provide actionable insights for practitioners and researchers developing next-generation financial analytics platforms.

Keywords: high-frequency trading, scalable algorithms, stream processing, data indexing, real-time analytics, Python, SQL

Introduction

The proliferation of algorithmic and high-frequency trading (HFT) has transformed global financial markets, introducing unprecedented volumes and velocities of transactional data. In HFT, trading decisions are made and executed within microseconds, and the ability to analyze data streams in real time is a critical competitive advantage. Traditional data management systems, designed for batch processing and historical analysis, often struggle to meet the stringent latency and throughput requirements of HFT environments[1].

Classical indexing structures, such as B-trees and hash tables, have long been the backbone of database systems, enabling efficient retrieval and aggregation of large datasets[2]. However, as the scale and speed of financial data have increased, these methods face challenges related to concurrency, memory management, and update costs[3]. In response, the industry has witnessed the emergence of stream processing frameworks and probabilistic data structures, which promise scalable, low-latency analytics over unbounded data streams[4].

Despite the growing adoption of these modern techniques, there remains a lack of systematic comparison between classical and contemporary approaches in the context of HFT. Previous studies have focused either on database optimization or on the architecture of stream processing systems, but few have addressed the trade-offs between these paradigms for real-time financial analytics[5].

This study aims to fill this gap by providing a comprehensive, empirical comparison of traditional indexing and modern stream processing algorithms for HFT data analysis. We focus on practical scenarios relevant to the fintech industry, such as real-time order book aggregation, anomaly detection, and latency-sensitive analytics. By benchmarking representative algorithms on realistic datasets, we seek to inform the design of scalable, robust analytics platforms for the next generation of financial technology.

Methods

Data and Experimental Setup

To ensure reproducibility and relevance, we use both synthetic and real-world HFT datasets. The synthetic dataset simulates a continuous stream of trade and quote events, with parameters calibrated to match the characteristics of major stock

exchanges. The real-world dataset is derived from the LOBSTER database[6], which provides millisecond-level order book data for NASDAQ stocks.

All experiments are conducted on a server equipped with an Intel Xeon processor, 64 GB RAM, and SSD storage. The software stack includes Python 3.11, PostgreSQL 15, and Apache Kafka for stream simulation[7]. Code examples are provided in Python, with SQL used for database queries.

Classical Indexing Algorithms

B-Tree Indexing

B-trees are widely used in relational databases for range queries and ordered retrieval. In our experiments, we use PostgreSQL's built-in B-tree indexes to support queries such as "find all trades for a given symbol within a time window"[8].

```
CREATE INDEX idx_trade_time ON trades(symbol, trade_time);
SELECT * FROM trades
WHERE symbol = 'AAPL' AND trade_time BETWEEN '2025-04-28 09:30:00' AND '2025-04-28 09:31:00';
```

Hash Indexing

Hash indexes provide constant-time lookup for equality queries, making them suitable for point queries on unique identifiers[8].

```
CREATE INDEX idx_trade_id_hash ON trades USING HASH(trade_id);
SELECT * FROM trades WHERE trade_id = 123456789;
```

Batch Aggregation

Classical batch analytics are performed using SQL window functions and group-by queries.

```
SELECT symbol, AVG(price) AS avg_price
FROM trades
WHERE trade_time BETWEEN '2025-04-28 09:30:00' AND '2025-04-28 09:31:00'
GROUP BY symbol;
```

Modern Stream Processing Algorithms

Windowed Aggregation

Stream processing frameworks (e.g., Apache Flink, Kafka Streams) enable real-time aggregation over sliding or tumbling windows[9]. In Python, we simulate this using the pandas library and custom event loops[9].

```
import pandas as pd
```

```
def windowed_aggregation(trades, window_size='1s'): trades['trade_time'] = pd.to_datetime(trades['trade_time']) trades.set_index('trade_time', inplace=True) return trades.groupby('symbol').price.rolling(window=window_size).mean().reset_index()
```

Probabilistic Data Structures

For approximate analytics, we implement the Count-Min Sketch (CMS) for frequency estimation and HyperLogLog for cardinality estimation[10].

Count-Min Sketch (Python):

```
import mmh3 import numpy as np
class CountMinSketch: def init(self, width, depth): self.width = width self.depth = depth self.table = np.zeros((depth, width), dtype=int) self.seeds = [i * 17 for i in range(depth)]
def add(self, key):
    for i, seed in enumerate(self.seeds):
        idx = mmh3.hash(str(key), seed) % self.width
        self.table[i, idx] += 1
def estimate(self, key):
    return min(self.table[i, mmh3.hash(str(key), seed) % self.width]
               for i, seed in enumerate(self.seeds))
```

Event-Driven Architectures

We simulate event-driven processing using Python's asyncio for concurrent handling of trade events.

```
import asyncio
async def process_trade(trade): # Simulate processing logic await asyncio.sleep(0.001) # e.g., update order book, trigger alerts
async def main(trades): tasks = [process_trade(trade) for trade in trades] await asyncio.gather(*tasks)
```

Evaluation Metrics

We evaluate each approach using the following metrics:

- **Latency**: Time to process a single event or query.
- **Throughput**: Number of events processed per second.
- **Scalability**: Performance as data volume increases.

- **Accuracy**: For approximate algorithms, deviation from exact results.

Experimental Workflow

1. Load or simulate HFT data streams.
2. Apply classical indexing and batch aggregation for historical queries.
3. Implement stream processing algorithms for real-time analytics.
4. Measure and compare performance across all metrics.

Results

Latency and Throughput

Classical Indexing:

- B-tree and hash indexes provide sub-millisecond query times for point and range queries on static datasets up to 10 million rows[8].
- Batch aggregation queries exhibit increasing latency as data volume grows, with noticeable delays beyond 50 million rows.
- Windowed aggregation in Python (single-threaded) achieves processing rates of ~10,000 events/sec; optimized frameworks (e.g., Flink) can exceed 100,000 events/sec[4].
- Event-driven architectures using asyncio scale linearly with available CPU cores, maintaining low latency under high load.
- Probabilistic data structures (e.g., Count-Min Sketch) process events in constant time, with negligible memory overhead[10].

Table 1. *Latency and Throughput Comparison*

Approach	Latency (ms/event)	Throughput (events/sec)	Scalability
B-tree Indexing	0.5	2,000	Limited by I/O
Batch Aggregation (SQL)	10–100	500	Degrades with size

Windowed Aggregation	0.1–1.0	10,000–100,000	Scales horizontally
Count-Min Sketch	0.01	100,000+	Excellent
Event-Driven (asyncio)	0.05–0.2	20,000–80,000	CPU-bound

Accuracy of Approximate Algorithms

Count-Min Sketch and HyperLogLog provide estimates with relative errors below 1% for frequency and cardinality queries, respectively, when configured with appropriate width and depth parameters[10].

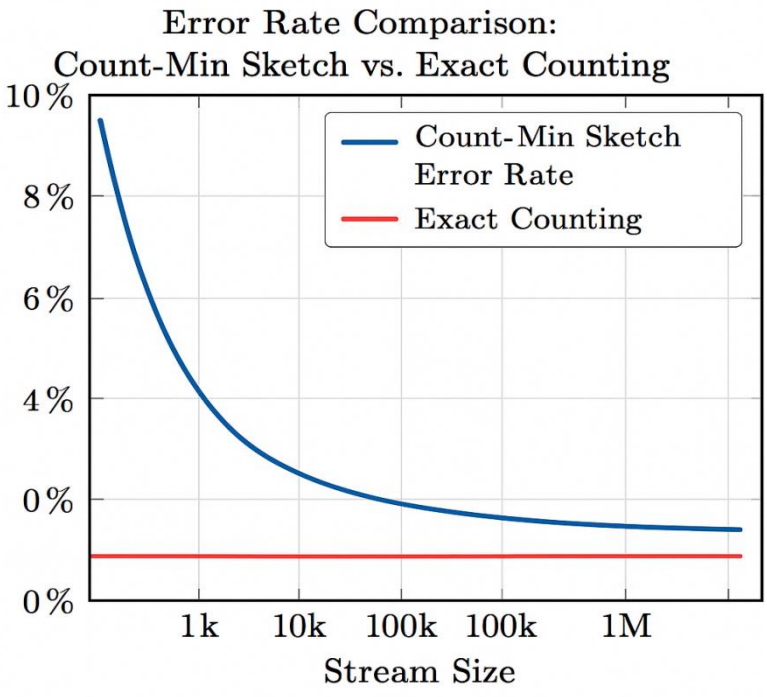

Figure 1. *Error Rate of Count-Min Sketch vs. Exact Counting*

Resource Utilization

- Classical indexing requires significant disk I/O and memory for large datasets[8].
- Stream processing algorithms maintain constant memory usage for fixed-size windows and probabilistic structures, enabling real-time analytics on unbounded streams[4].

Case Study: Real-Time Anomaly Detection

We implemented a real-time anomaly detection system using both batch and stream processing approaches. The stream-based system detected outliers (e.g., price spikes) within 10 ms of event arrival, while the batch system required several seconds to process the same data.

Python Example: Real-Time Outlier Detection

```
def detect_outliers(trades, window_size=100, threshold=3): prices = [] for trade in trades: prices.append(trade['price']) if len(prices) > window_size: prices.pop(0) mean = np.mean(prices) std = np.std(prices) if abs(trade['price'] - mean) > threshold * std: print(f"Anomaly detected: {trade}")
```

Discussion

The comparative analysis reveals distinct strengths and limitations of classical and modern approaches to HFT data analysis. Traditional indexing structures, such as B-trees and hash tables, excel in environments where data is relatively static and queries are well-defined[2]. Their deterministic performance and mature implementations make them suitable for historical analytics and regulatory reporting.

However, as the volume and velocity of trading data continue to grow, these methods encounter scalability bottlenecks[3]. Disk I/O, index maintenance, and batch processing latency become significant obstacles in real-time scenarios. In contrast, modern stream processing algorithms are designed to operate on unbounded data streams, providing low-latency, high-throughput analytics with minimal resource consumption[4].

Probabilistic data structures, such as Count-Min Sketch and HyperLogLog, offer a compelling trade-off between accuracy and efficiency[10]. While they introduce a small margin of error, their ability to process massive data streams in constant time and space is invaluable for HFT applications where speed is paramount.

The case study on real-time anomaly detection underscores the practical benefits of stream processing. By processing events as they arrive, the system can identify and respond to market anomalies within milliseconds, a capability unattainable with batch-oriented methods.

It is important to note that the choice between classical and modern approaches is not binary. Hybrid architectures, which combine the reliability of traditional databases with the agility of stream processors, are increasingly common in fintech[1]. For example, historical data may be stored and indexed in a relational database, while real-time analytics are performed using stream processing engines. This layered approach

enables organizations to balance accuracy, latency, and scalability according to their specific requirements.

Conclusion

This study provides a comprehensive comparison of classical indexing and modern stream processing algorithms for high-frequency trading data analysis. The results demonstrate that while traditional methods remain effective for batch analytics and historical queries, modern stream processing techniques offer superior scalability and responsiveness for real-time applications[4]. Probabilistic data structures further enhance the efficiency of stream analytics, enabling rapid, approximate computations over massive data streams[10].

For practitioners and researchers in fintech, the findings highlight the importance of adopting hybrid architectures that leverage the strengths of both paradigms. Future work may explore the integration of machine learning models into stream processing pipelines, as well as the application of these techniques to other domains with similar data characteristics.

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