

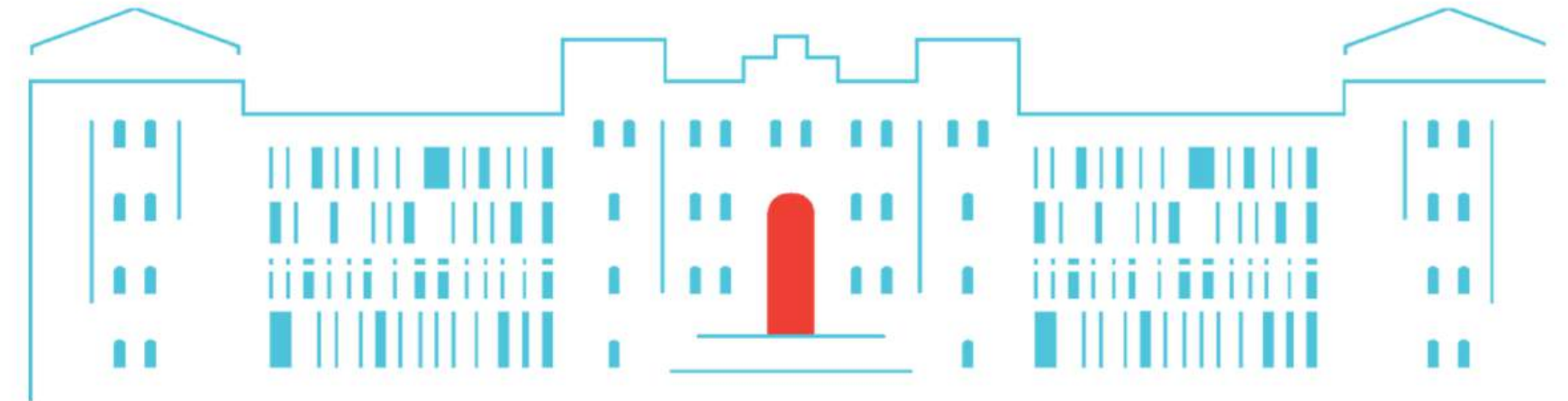
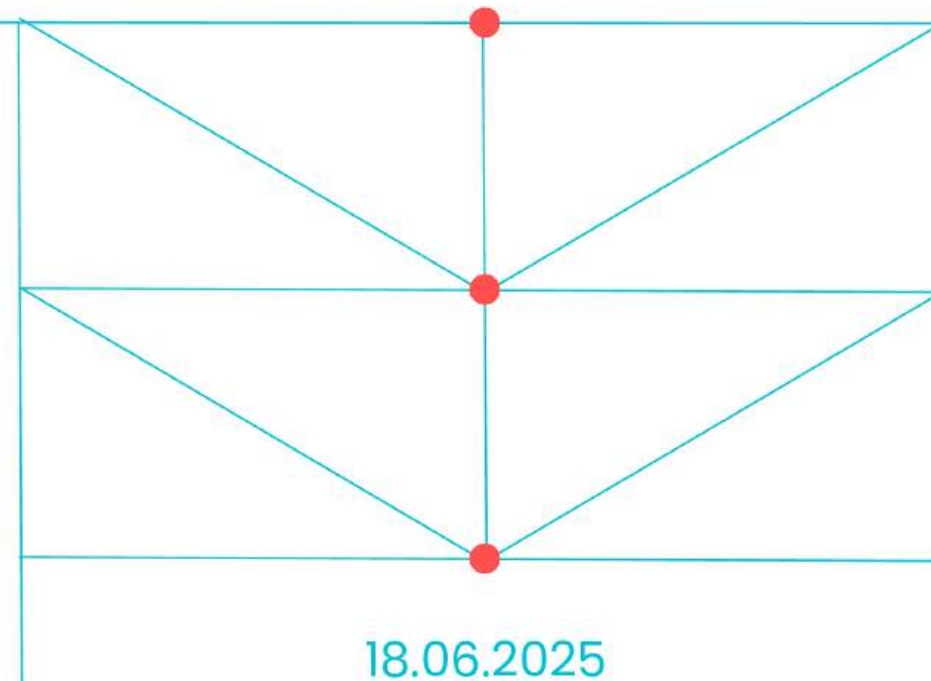
BD25_Project_F4_B

Real-Time Traffic Monitoring

Final Presentation

Big Data PBL (SoSe25)

TUHH
Technische
Universität
Hamburg



Presented by:

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Meet the Team



Gayathri
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Manali
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Ravi
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Shinu
Shaju

Project Goal & Objectives

- Build a real-time, scalable system to monitor 10,000+ taxis live in Beijing using taxi GPS trajectory data
- Process high-throughput, continuous data streams with low latency
- Compute taxi speed, average speed, distance run, and violation alerts in real-time
- Present actionable insights live on a responsive dashboard for large-scale taxi fleet monitoring
- Design for scalability, fault tolerance, and future extensibility

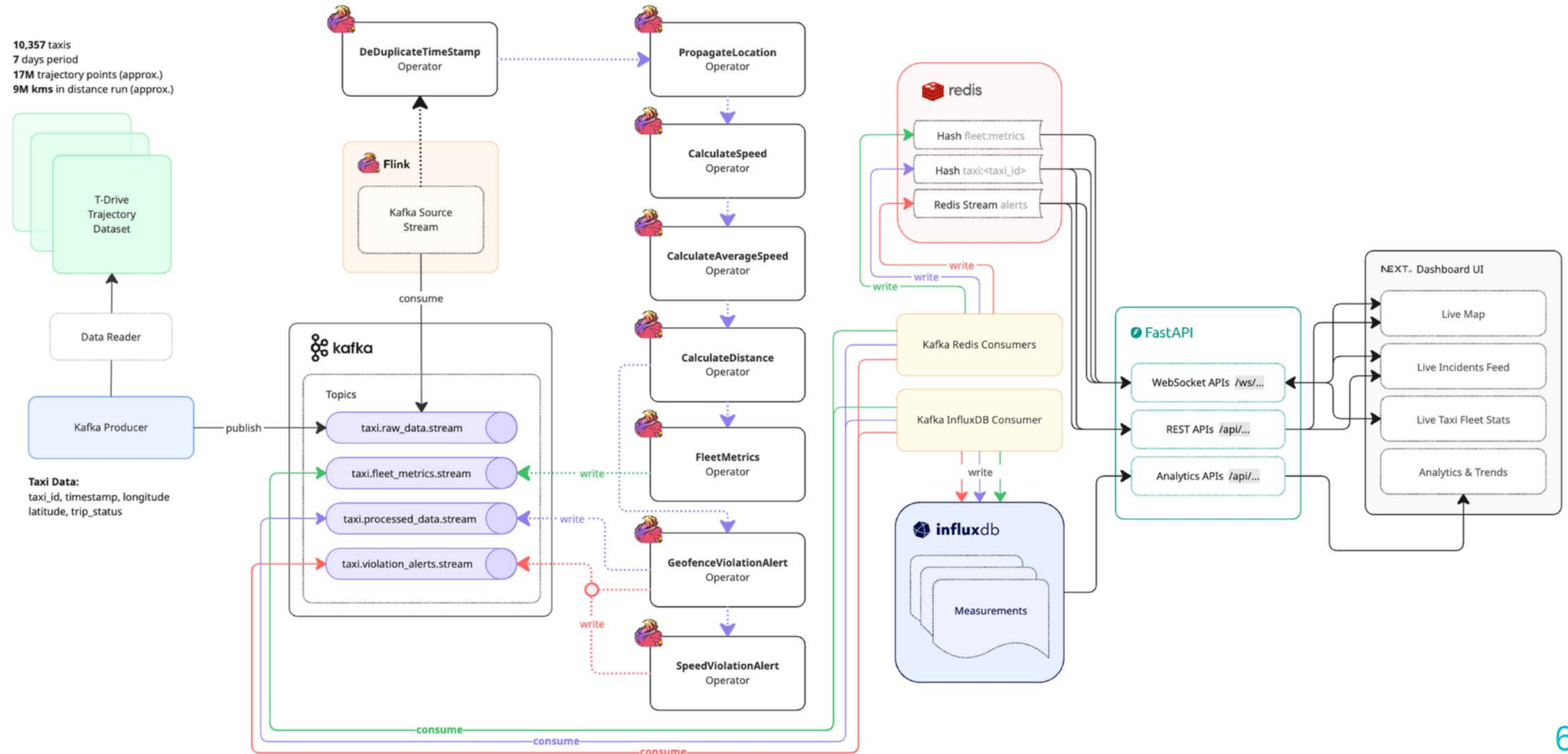
Dataset Overview

- **T-Drive Trajectory Dataset** (Microsoft Research), Beijing, 2008
- **10,357** taxis, **~17M** taxi GPS data points over **7 days**, **~9M** total distance run
- Features: taxi_id, timestamp, latitude, longitude
- Provides high-frequency taxi updates to enable controlled real-time data ingestion
- Serves as a reliable ground truth for urban mobility systems under realistic conditions

Key Challenges

- **High Throughput:** Processing 17M+ GPS points from 10000+ taxis with a goal of lowest latency possible
- **Data Quality:** Handling invalid and null data gracefully without disrupting pipeline flow or compromising data quality
- **Real-Time Guarantees:** Deliver continuous, low-latency insights to end-users without delays
- **State Management:** Tracking each taxi's prior location data for computing speed, distance, and speed and geofence violations incidents
- **Scalability vs. Accuracy:** Balancing resources while maintaining stability and correctness under load
- **Fault Tolerance:** Recover reliably and quickly from failures without any data loss

System Architecture



System Architecture

DataReader:

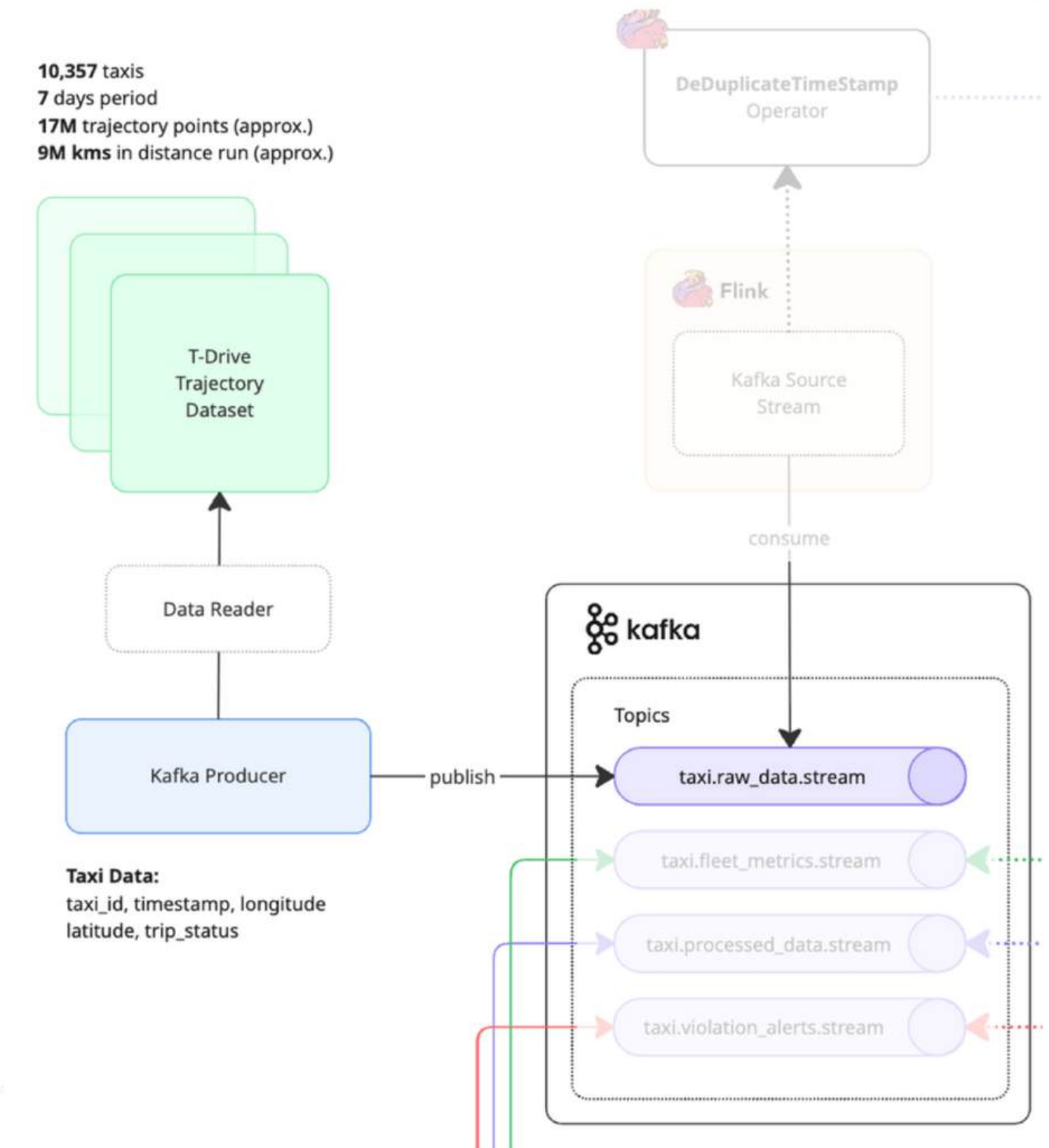
- Adds a trip_status field (active/end) to a taxi message
- Sorts records by timestamp for event-time correctness
- Serializes entire data as fast-loading pickle file
- Supports dataset size limit for controlled testing

Apache Kafka Producer:

- Supports high-throughput data streaming to match pipeline capacity
- Two data replay modes (actual event delays, simulated 1s)
- Data ingestion speed controls (1x–3x)
- Batches all records with same timestamp for efficiency

Kafka Broker:

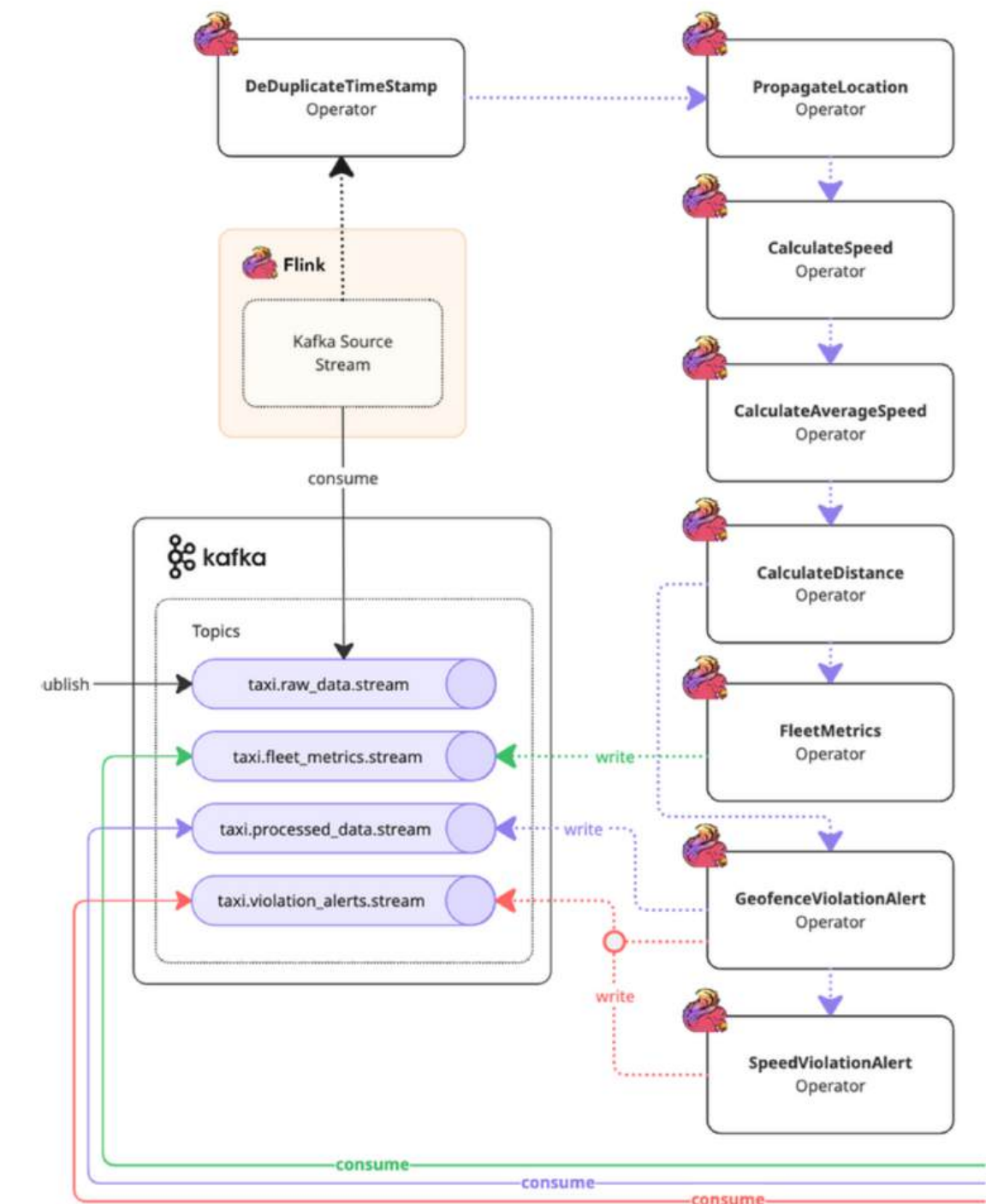
- Deployed in KRaft mode (1 broker)
- Automated creation of Kafka topics with docker init container
- Web UI for monitoring



System Architecture

Apache Flink DataStream Pipeline & Operators:

- Built and deployed a custom Docker image to support PyFlink DataStream APIs for efficient pipeline execution
- 1 x JobManager, 1 x TaskManager (parallelism = 1, task slots = 1)
- Docker init container to automate flink job creation & execution
- Kafka source connector creates datastream from source topic
- Source stream undergoes transformations by sequential operators
- Kafka sink connector sinks datastreams to target topics
- Event-time processing with monotonic watermarks
- Embedded RocksDB for state backend
- Incremental checkpointing for fault tolerance
- Web UI for monitoring and debugging



System Architecture

Kafka Consumers:

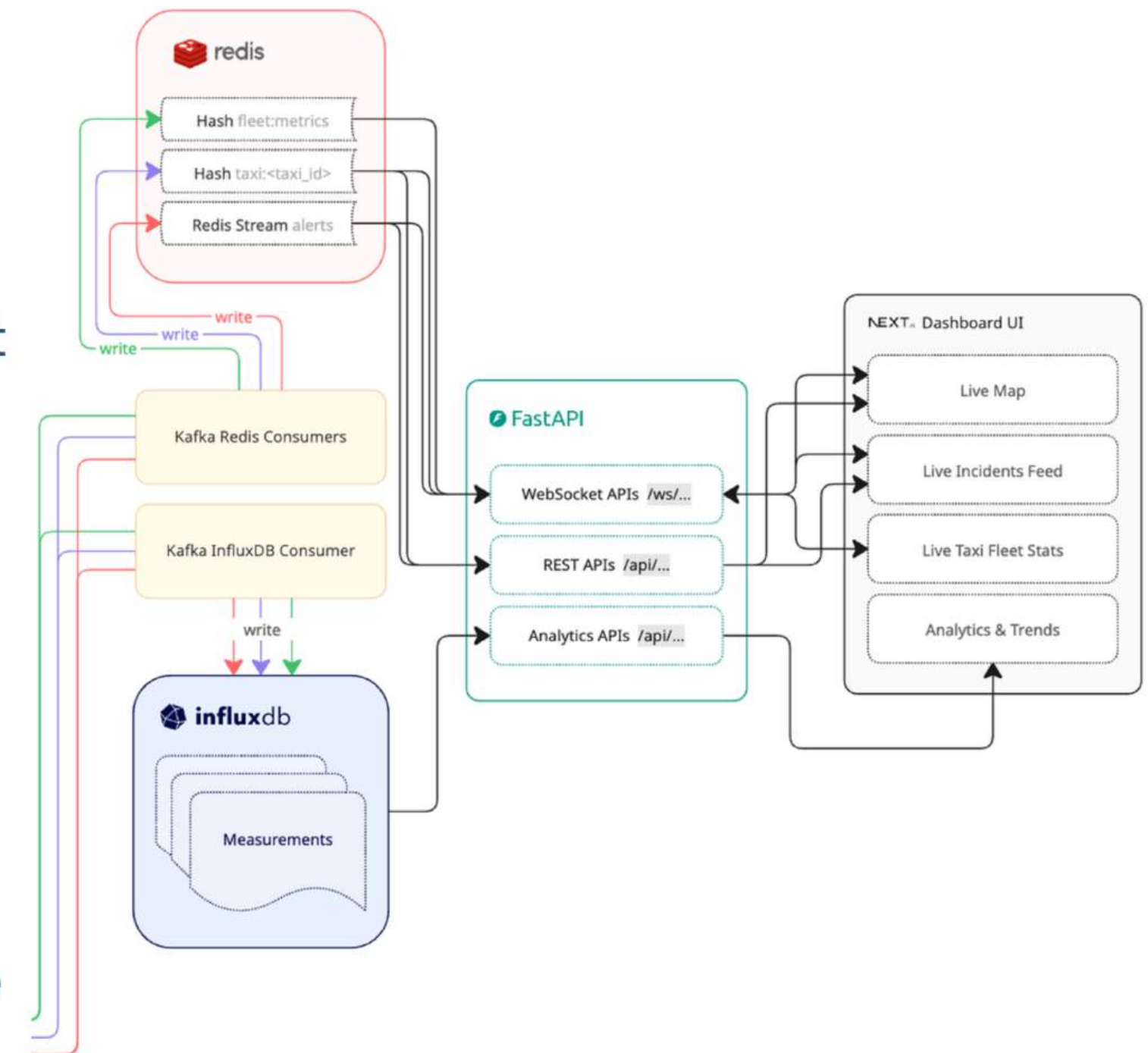
- Redis:
 - Redis Hash for caching taxi data and fleet metrics
 - Redis Streams for storing taxi violation alerts
- InfluxDB:
 - Uses InfluxDB Measurements for storing taxi data, fleet metrics and violation alerts for analytics

FastAPI Backend APIs:

- REST + WebSocket APIs for live & historical taxi data, violation alerts and analytics

NextJS Dashboard UI:

- Interactive map with Leaflet + clustering for scalable, responsive taxi tracking under load
- Live and historical incidents feed for speed and geofence violation alerts
- Taxi fleet-level and per-taxi metrics and analytics



Initial DataStream Pipeline Performance Challenges

- High and increasing latency, hindering real-time responsiveness
- Persistent operator tasks backpressure and growing consumer lag under high load
- Unbounded state & timer growth in operators, increasing memory, resource usage and latency
- Performance degraded under load beyond 3,000 taxis due to throughput limits
- Unable to achieve low and stable latency while scaling to 9,000+ taxis

DataStream Pipeline Optimization Strategies

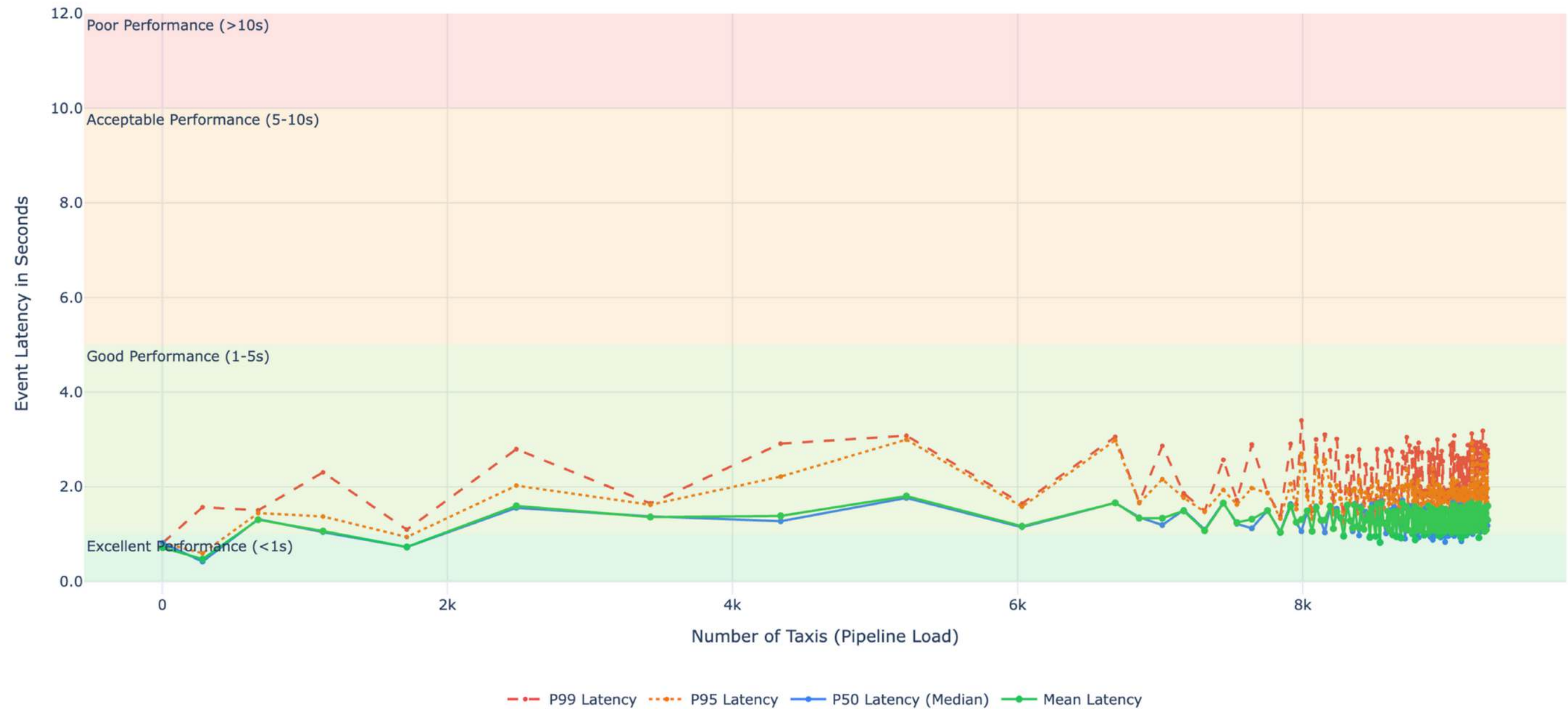
- **PropagateLocation Logic:** Replaced timers with timestamp-based emission to prevent backpressure
- **Monotonic Watermarks:** Reduced latency by avoiding out-of-order and late arrival waits
- **DataStream Serialization & Deserialization:** Parsed Kafka JSON messages once at the Kafka source to a structured data, avoiding repeated serialization/deserialization in downstream operators
- **Fast Serialization:** Switched to orjson instead of standard json for faster, low-CPU serialization
- **EmbeddedRocksDB State Backend:** Enabled scalable, disk-backed state with incremental checkpoints
- **TaskManager Memory Tuning:** Increased managed memory, tuned network buffers for load
- **Frequent Checkpointing:** Incremental checkpoints (every 1s) for fast recovery with minimal overhead
- **State Cleanup:** Cleared trip ended taxis state in operators to prevent state bloat
- **Early Propagation:** Moved PropagateLocation operator to pipeline start to reduce downstream load

Performance Test: Setup and Benchmarking

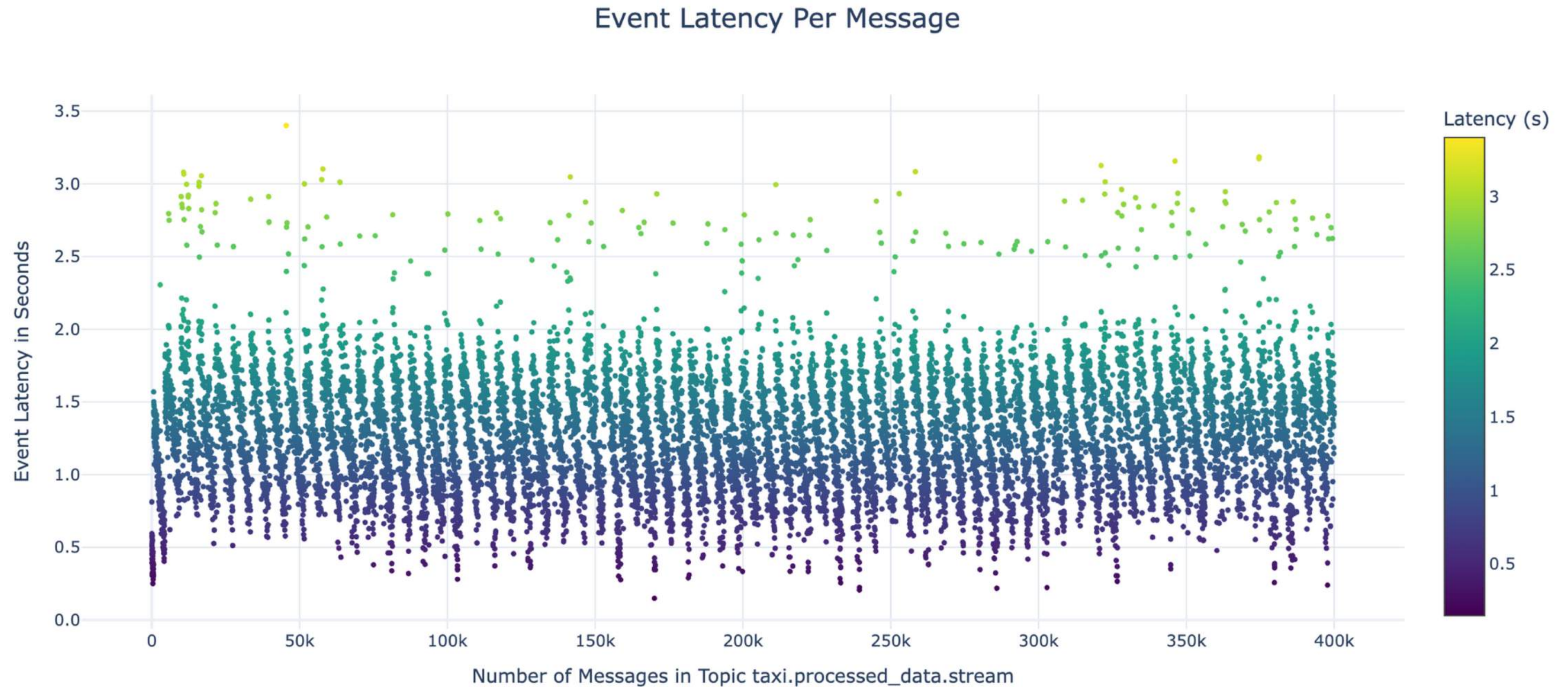
- **Benchmarking Measurements:**
 - **Event Latency:** Time from message ingestion to Kafka source topic (T1) to processing and sinking datastream to Kafka target topics (T2)
 - **Pipeline Throughput:** messages processed per second (40 msgs/s)
 - **Load simulation:** Variable taxi count over time (upto 10,000+ simultaneous taxis).
- **Performance Test Environment & Configurations:**
 - **Hardware Specifications:** 4 vCPU, 16GB RAM, 50GB SSD
 - **Kafka and Flink Configuration:** parallelism = 1, partitions = 1, task slots = 1
 - **Data Replay Configuration:** simulated mode at 1x speed, max 10,357 taxis
 - **Data Volume:** 400,000 messages processed over a 2-hour runtime
- **Custom Benchmarking Tool:** Developed a custom benchmarking tool to measure key metrics such as event latency vs load, event latency per message, and throughput vs event latency graphs

Performance Test: Results and Analysis

Pipeline Performance Analysis: Event Latency vs Pipeline Load with Percentiles

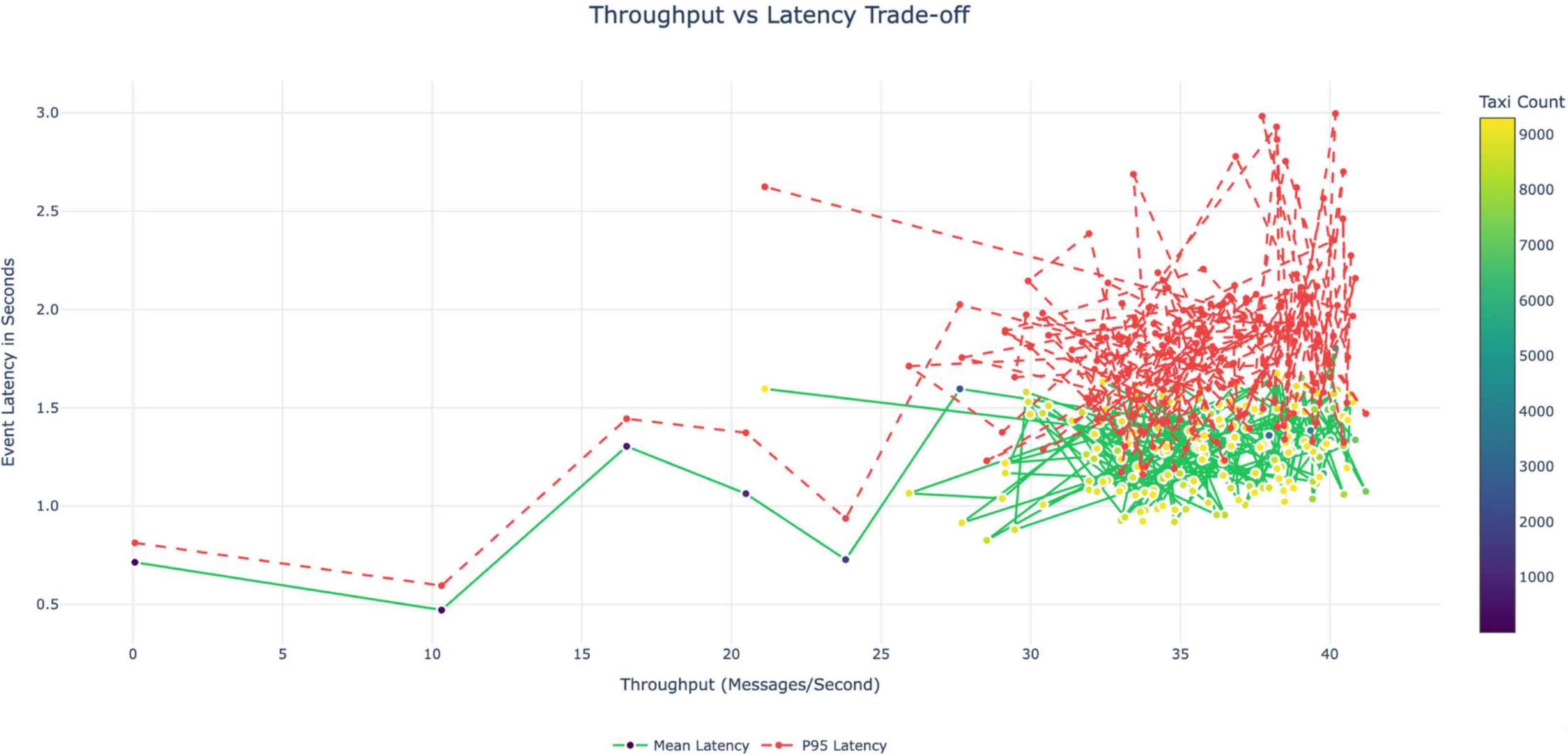


Performance Test: Results and Analysis



- Event Latency Per Message

Performance Test: Results and Analysis



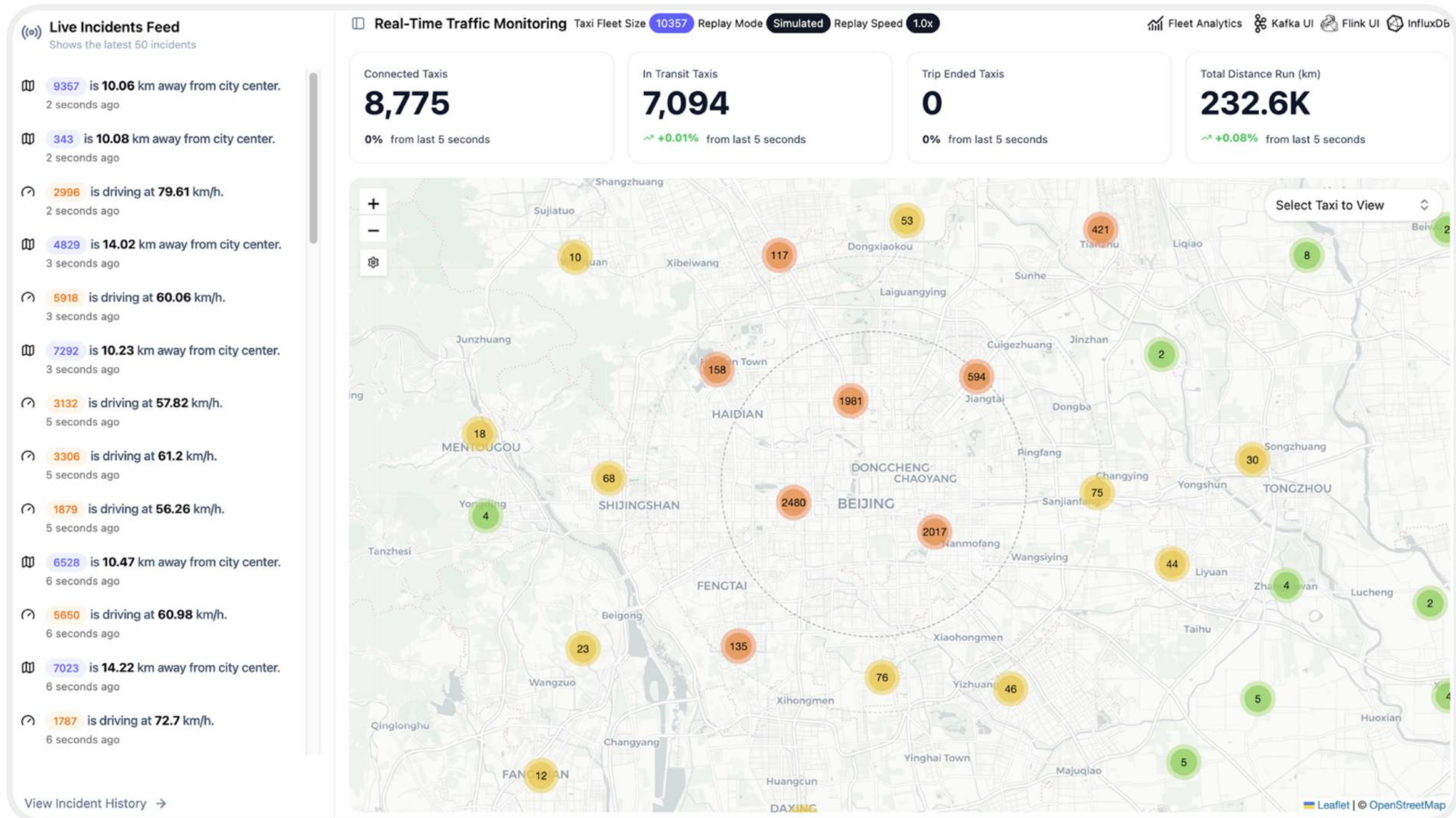
Performance Test: **Key Insights**

- **Consistent Low Latency:** Processes 95% of messages within 2 seconds across all loads
- **Predictable Latency Growth:** Stable latency increase from low to higher test loads
- **Resilience:** Minor latency spikes at peak load, but quickly recover
- **Throughput-Latency Balance:** Efficiently handles medium to high workloads
- **No Backpressure:** Operators run with low utilization and smooth data flow
- **Fast Checkpointing:** Incremental RocksDB checkpoints complete in <1s
- **Stable Performance:** Achieves stable performance with simple pipeline setup
- **Scalable Real-Time Monitoring:** Supports reliable taxi fleet monitoring at scale

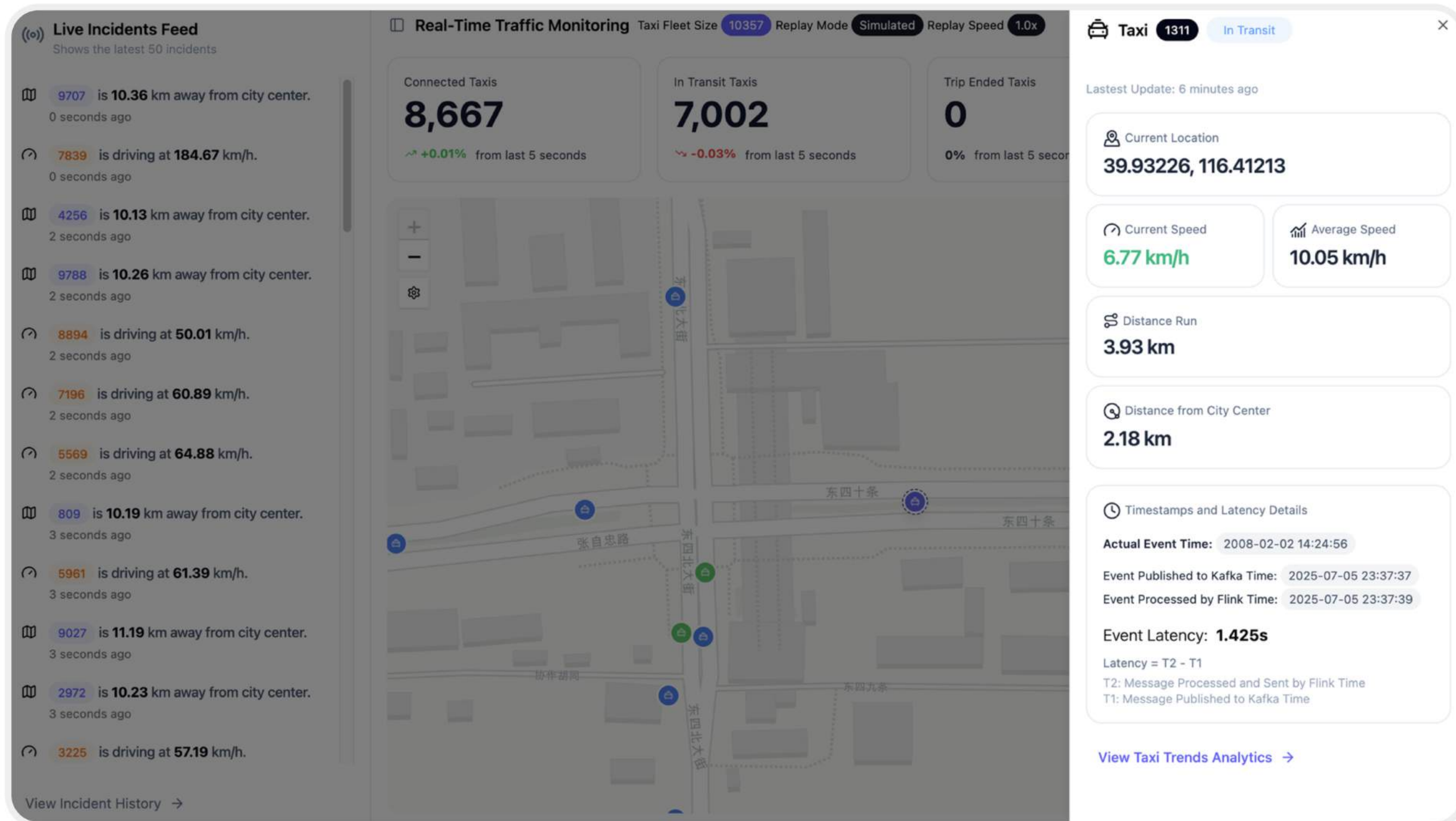
Extended Load Testing & Future Scaling

- **Extended Load Test:** At 3X replay speed (~120 msgs/s, 10,357 taxis), latency spiked sharply (60–250s) before stabilizing, indicating natural saturation near system capacity
- **Resilience Under High Load:** Longer busy periods and occasional backpressure observed for operator tasks, but the pipeline recovered quickly and remained stable
- Scaling checklist for higher throughput with low latency:
 - **TaskManager Scaling:** Increase TaskManager count and memory
 - **Increase Kafka Partitioning:** Use multi-partition topics for better load distribution
 - **Increase Parallelism & Task Slots:** Adjust operator parallelism and task slot allocation
 - **State Backend Optimization:** Tune RocksDB and checkpoint settings for high throughput
 - **Auto-Scaling:** Enable Flink dynamic scaling based on ingestion rates
 - **Dedicated VM Deployment:** Run high-load services on dedicated VMs for isolation and efficiency

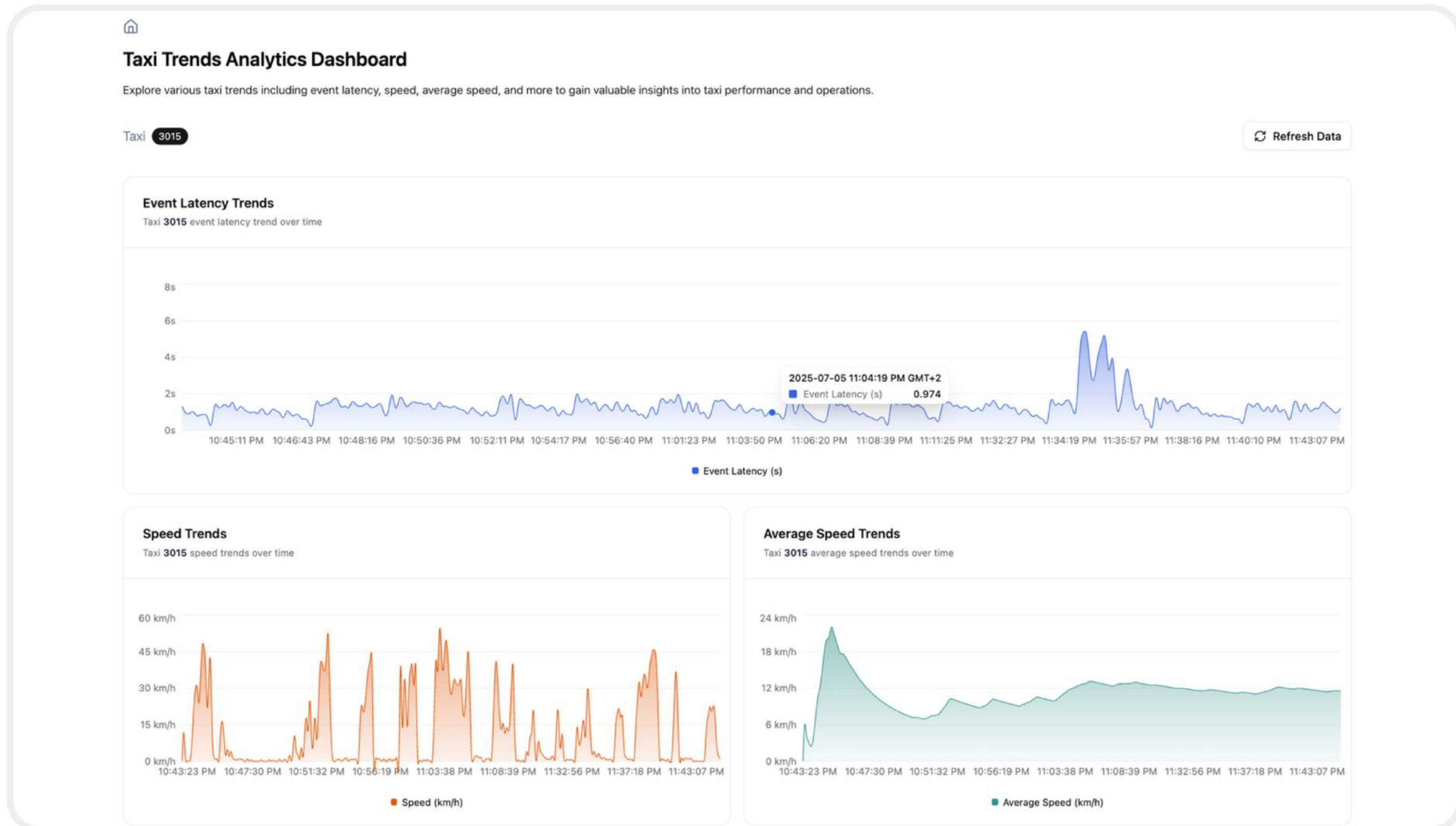
Dashboard Key Features: Live Fleet Monitoring



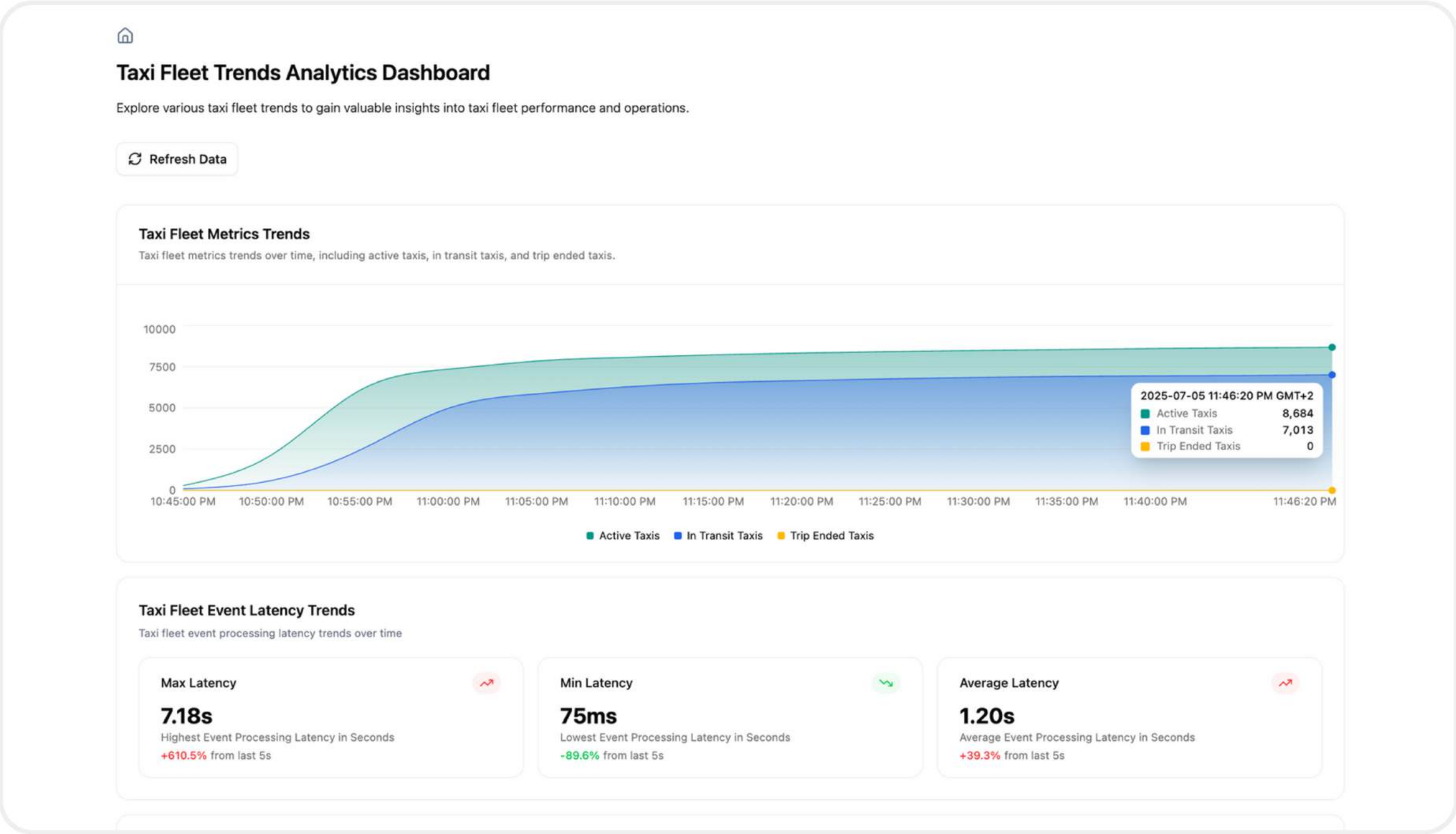
Dashboard Key Features: Per-Taxi Monitoring



Dashboard Key Features: Per-Taxi Analytics



Dashboard Key Features: Taxi Fleet Analytics



Dashboard Key Features: Incidents History



Incidents

Total Incidents: 4426 Geofence Violations: 2513 Speed Violations: 1913

Refresh Incidents

Taxi ID	Event	Timestamp	Actual Event Time	Current Coordinates [Lat, Lng]		Taxi Status
7740	speed_violation Taxi is driving at 51.86 km/h.	2025-07-01 11:21:47	2008-02-02 14:09:12	116.50778	40.01	active
7470	geofence_violation Taxi is 10.8 km away from city center.	2025-07-01 11:21:47	2008-02-02 14:09:14	116.28232	39.95712	active
10335	geofence_violation Taxi is 11.69 km away from city center.	2025-07-01 11:21:47	2008-02-02 14:09:13	116.45051	40.01315	active
7740	geofence_violation Taxi is 14.05 km away from city center.	2025-07-01 11:21:47	2008-02-02 14:09:12	116.50778	40.01	active
9375	speed_violation Taxi is driving at 59.18 km/h.	2025-07-01 11:21:44	2008-02-02 14:09:10	116.36329	39.96627	active
8767	geofence_violation Taxi is 11.17 km away from city center.	2025-07-01 11:21:44	2008-02-02 14:09:11	116.39371	39.81585	active
3316	geofence_violation Taxi is 10.72 km away from city center.	2025-07-01 11:21:44	2008-02-02 14:09:09	116.47845	39.9899	active
8554	speed_violation Taxi is driving at 119.29 km/h.	2025-07-01 11:21:41	2008-02-02 14:09:08	116.36673	39.8985	active
1277	speed_violation Taxi is driving at 53.69 km/h.	2025-07-01 11:21:41	2008-02-02 14:09:08	116.42946	39.90442	active
8549	speed_violation Taxi is driving at 50.01 km/h.	2025-07-01 11:21:41	2008-02-02 14:09:08	116.30526	39.94069	active
366	speed_violation Taxi is driving at 54.45 km/h.	2025-07-01 11:21:41	2008-02-02 14:09:08	116.46856	39.83864	active
4539	geofence_violation Taxi is 10.39 km away from city center.	2025-07-01 11:21:41	2008-02-02 14:09:07	116.46119	39.99579	active

Let's see it live... 🚀

Conclusion & Key Achievements

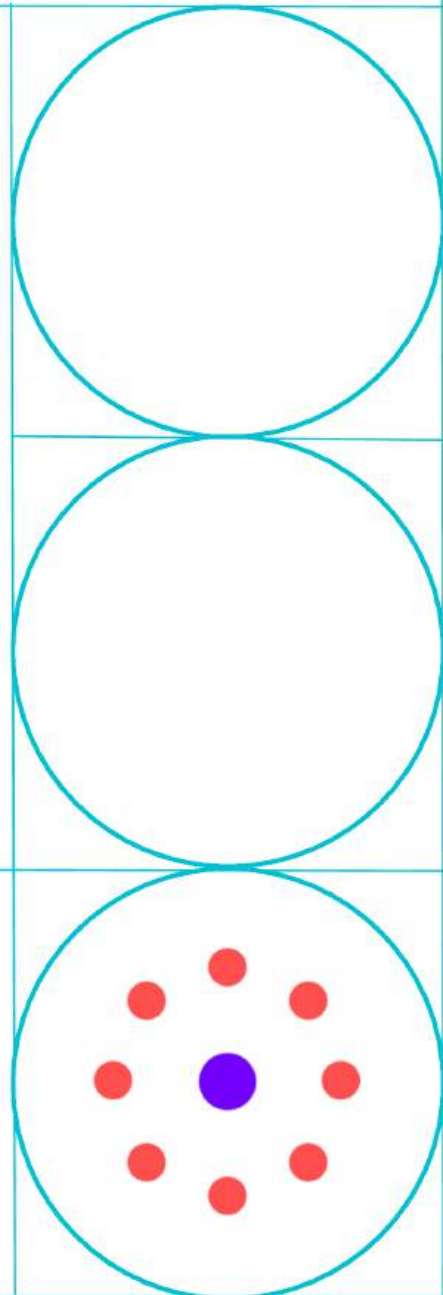
- Transformed slow system into a fast, scalable real-time taxi fleet monitoring platform
- Reduced average event processing time from ~35s or higher to <2s per message
- Supports 9,000+ taxis simultaneously without performance degradation
- 95% of messages processed within 2s across all load levels
- Smooth pipeline operation with no bottlenecks under heavy load
- Fast RocksDB checkpointing (<1s) ensures quick failure recovery
- Improvements are driven by optimized state management, memory tuning, and operator design
- System is reliable and ready for real-time taxi fleet traffic monitoring systems

Questions?

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Thank You!

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