

StreamQL: A Query Language for Efficient Data Stream Processing

Lingkun Kong, Konstantinos Mamouras Rice University



Motivation

Big-data era: IoT applications such as predictive maintenance collect, process and analyze a massive amount of data in real-time.

- The setting of data stream processing
- unbounded source of data
- real-time, very high rate
- complex patterns
- Low-level stream processing using general-purpose programming language is cumbersome, error-prone, and not modular.



State of the Art

Streaming Database: STREAM, Aurora, Borealis, CACQ, TelegraphCQ, Niagara, Gigascope, Nile, StreamInsight		Complex Event Processing: SQL-TS, SASE, Cayuga, SPL MatchRegex, Zstream, Trill, Esper, Siddhi, <u>Flink</u> , Oracle Stream Analytics, IBM Streams	
Distributed Stream Processing: S4, IBM Streams, MapReduce Online, Storm, Heron, Samza, Naiad, Spark Streaming, Flink, Google's MillWheel, Apex	S	ignchronous Dataflow: SIGNAL, Esterel, LUSTRE, StreamIt Light-weight Streaming Engine: Microsoft o Trill	
	Rea Xst	II-time Signal Processing: ream, WaveScope, TrillDSP	Esper, Siddhi, ReactiveX StreamORE

- Limitations:
- Lack of stream abstractions and formal semantics.
- No guarantee of correctness.
- Inefficient in detecting complex patterns.

Our Approach

- StreamQL (Streaming Query Language) simplifies the task of specifying complex streaming computations.
- Stream processing is a procedure that transforms the input stream to the output stream.



- Contributions:
- economical (only half size of RxJava)
- proved to be expressive and correct.
- **better throughput performance** in practice in comparison to other state-of-the-art approaches.
- signal processing and machine learning toolbox.

Relational	Dataflow	Temporal
nap, filter, emit, aggr, groupBy, window	compose, parallel	take, skip, search, seq, iterate

Case Studies

- **Predictive maintenance:**
- Rolling Bearing Fault Prediction
- Battery Aging
- Healthcare Monitoring:
- Cardiac Signal analysis
- Arterial Blood Pressure monitoring
- Walking motion detection
- High-frequency Market Analysis:
- Trading direction analysis

Example of Predictive Maintenance:

- pipeline-styled streaming computation
- windowing and key-based partitioning
- signal processing support
- machine learning support



getMagn = map(x -> sqrt(x.ax*x.ax+x.ay*x.ay+x.az*x.az)/3.0); smoothing = FIR([... fir parameters ...]); bandpass = IIR([... bandpass filtering parameters ...]); envelope = HT(... Hilbert transform parameters ...) >> abs(); spectrum = window(n, s, FFT(... FFT parameters ...)); getFeatures = getMagn >> smoothing >> bandpass >> envelope >> spectrum;

training = SVM(... training parameters ...); detecting = ...; singleProc = getFeatures >> seq(training, detecting); process = groupBy(x -> x.id, singleProc, (key,res) -> ...);

Experiments

- The Java implementation of StreamQL is evaluated with RxJava and Siddhi in one micro benchmark and four benchmarks with realistic workloads.
- Micro Benchmark: For basic stream computations, StreamQL is 1.1-100 times faster than RxJava and 2–100 times faster than Siddhi.
- Realistic Workloads: For computations involving complex streaming aggregation and pattern detection, StreamQL is on average 5 times faster than RxJava and 40 times faster than Siddhi.