EXPERIENCES WITH STREAMING & MICRO-BATCH FOR ONLINE LEARNING

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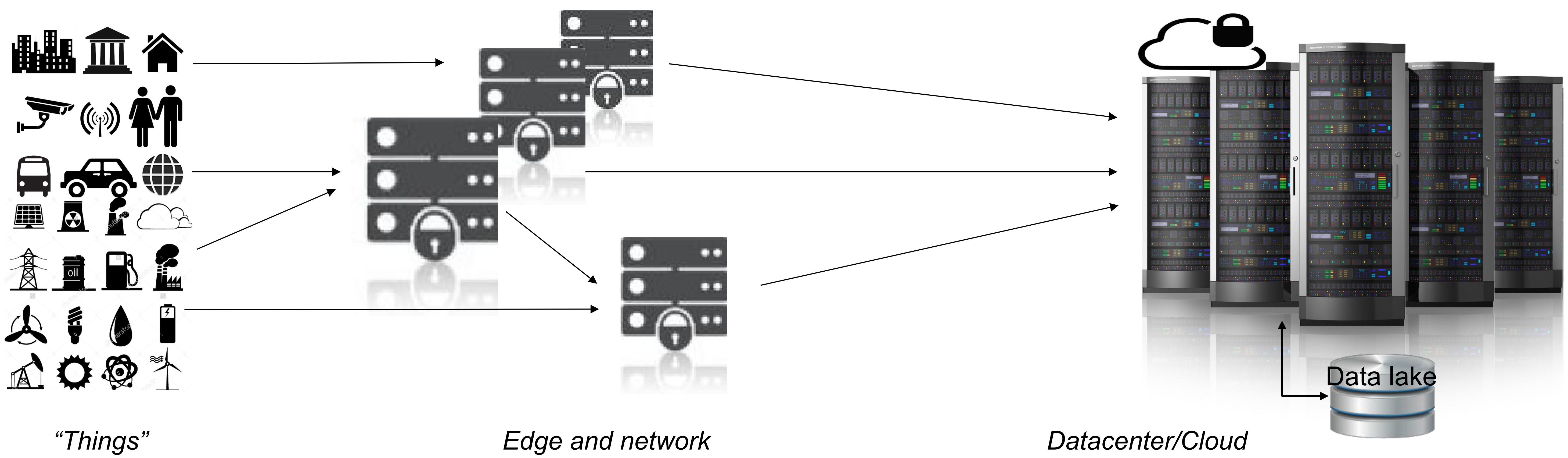
Powering Machine Learning

The Challenge of Today's Analytics Trajectory

IoT is Driving Explosive Growth in Data Volume



Edges benefit from real-time online learning and/or inference

Real-Time Intelligence: Online Algorithm Advantages

- **Real-world data is unpredictable and bursty**
  - Data behavior changes (different time of day, special events, flash crowds, etc.)
- **Data behavior changes require retraining & model updates**
  - Updating models offline can be expensive (compute, retraining)
- **Online algorithms retrain on the fly with real-time data**
  - Lightweight, low compute and memory requirements
  - Better accuracy through continuous learning
- **Online algorithms are more accurate, especially with data behavior changes**

Experience Building ML Algorithms on Flink 1.0

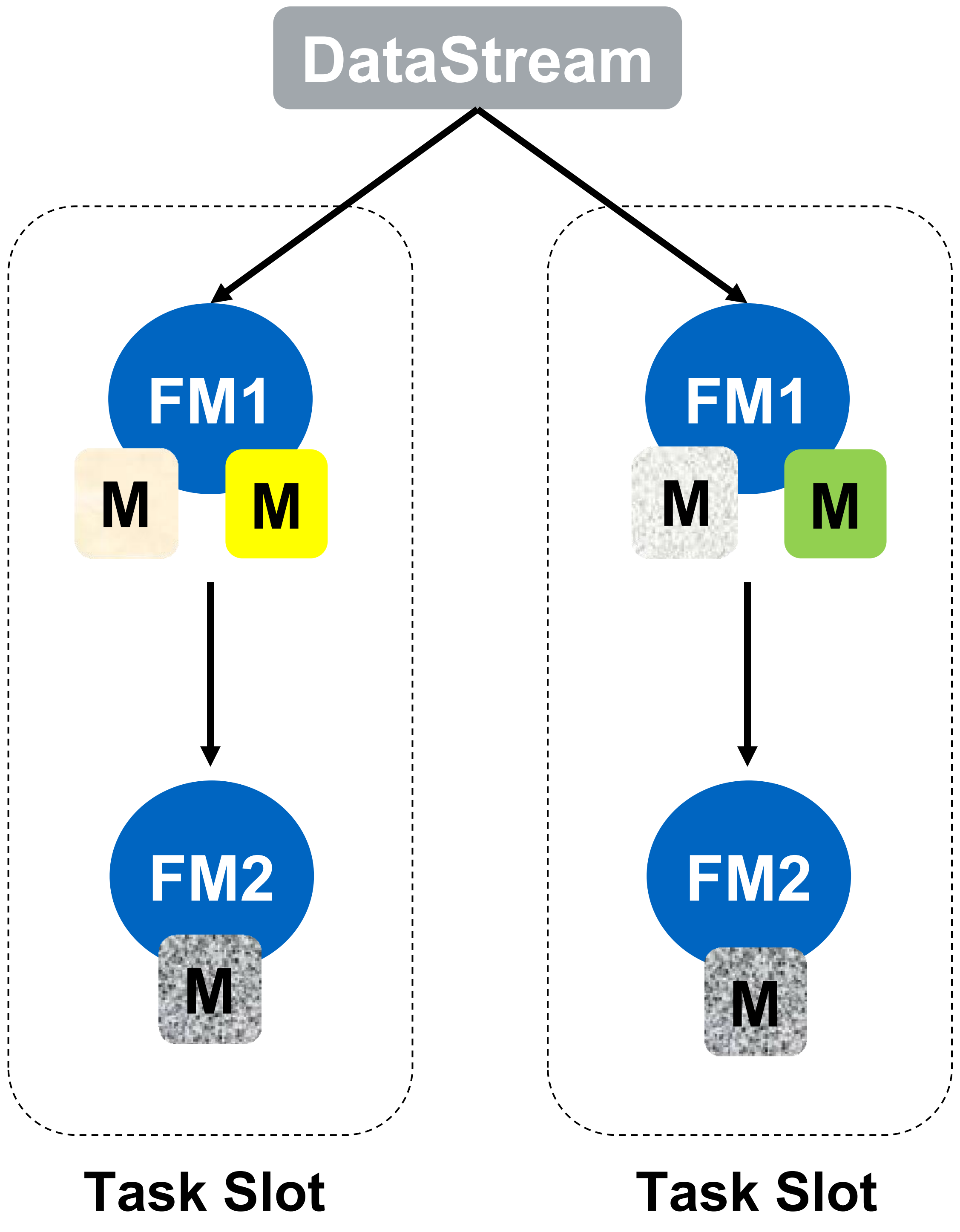
- Built both Offline(Batch) and Online algorithms
  - Batch Algorithms (Examples: KMeans, PCA, and Random Forest)
  - Online Algorithms (Examples: Online KMeans, Online SVM)
- Uses many of the Flink DataStream primitives:
  - DataStream APIs are sufficient and primitives are generic for ML algorithms.
  - CoFlatMaps, Windows, Collect, Iterations, etc.
- We have also added Python Streaming API support in Flink and are working with dataArtisans to contribute it to upstream Flink.

Example: Online SVM Algorithm

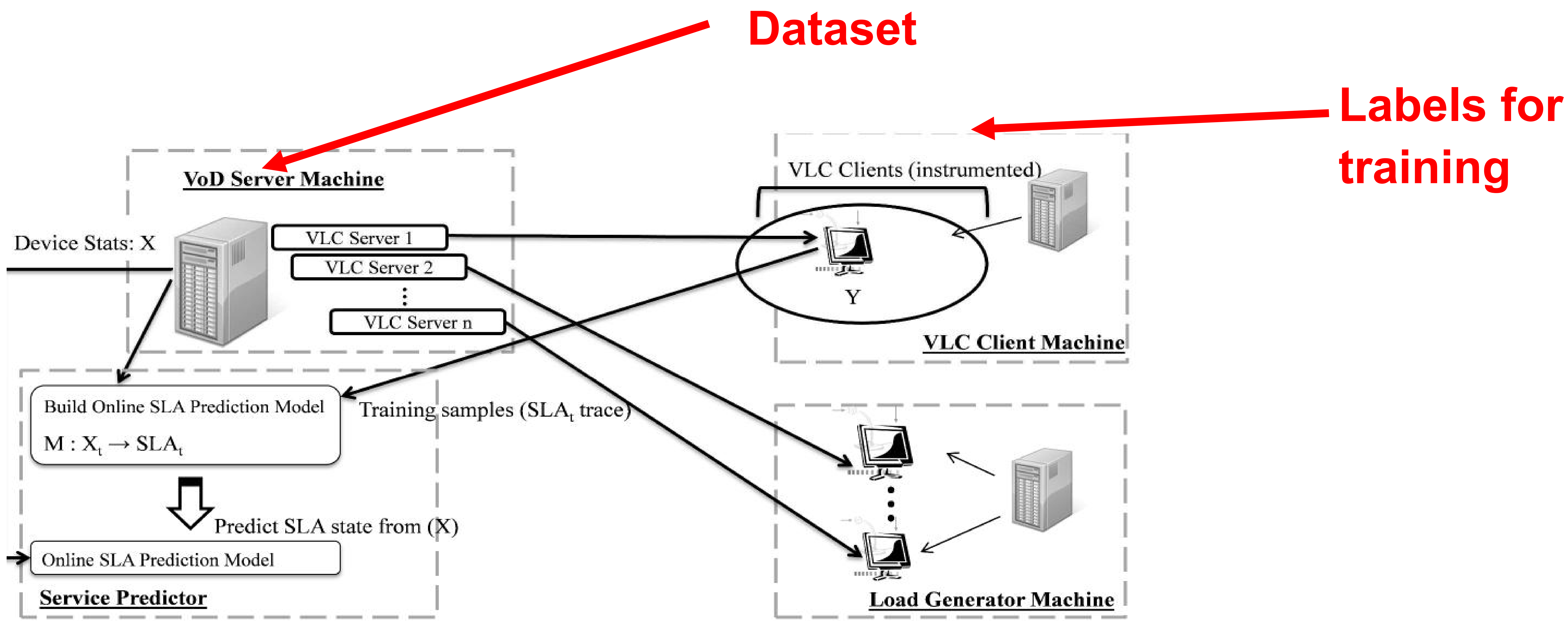
```
/* Co-map to update local model(s) when new data arrives and also
create the shared model when a pre-defined threshold is met */
private case class SVMModelCoMap(...) {
    /* flatMap1 processes new elements and updates local model*/
    def flatMap1(data: LabeledVector[Double],
                 out: Collector[Model]) {
        . . .
    }
    /* flatMap2 accumulates local models and creates a new model
(with decay) once all local models are received */
    def flatMap2(currentModel: Model, out: Collector[Model]) {
        . . .
    }
}

object OnlineSVM {
    . . .
    def main(args: Array[String]): Unit = {
        // initialize  input arguments and connectors
        . . .
    }
}
```

Aggregated and local models combined with decay factor



Telco Example: Measuring SLA Violations



- A server providing VoD services to VLC (i.e., media player) clients
  - Clients request videos of different sizes at different times
  - Server statistics used to predict violations
- **SLA violation:** service level drops below predetermined threshold

Dataset

(https://arxiv.org/pdf/1509.01386.pdf)

CPU Utilization	**Memory/Swap**	**I/O Transactions**	**Block I/O operations**	**Process Statistics**	**Network Statistics**
CPU Idle	Mem Used	Read transactions/s	Block Reads/s	New Processes/s	Received packets/s
CPU User	Mem Committed	Write transactions/s	Block Writes/s	Context Switches/s	Transmitted Packets/s
CPU System	Swap Used	Bytes Read/s			Received Data (KB)/s
CPU IO_Wait	Swap Cached	Bytes Written/s			Transmitted Data (KB)/s
					Interface Utilization %

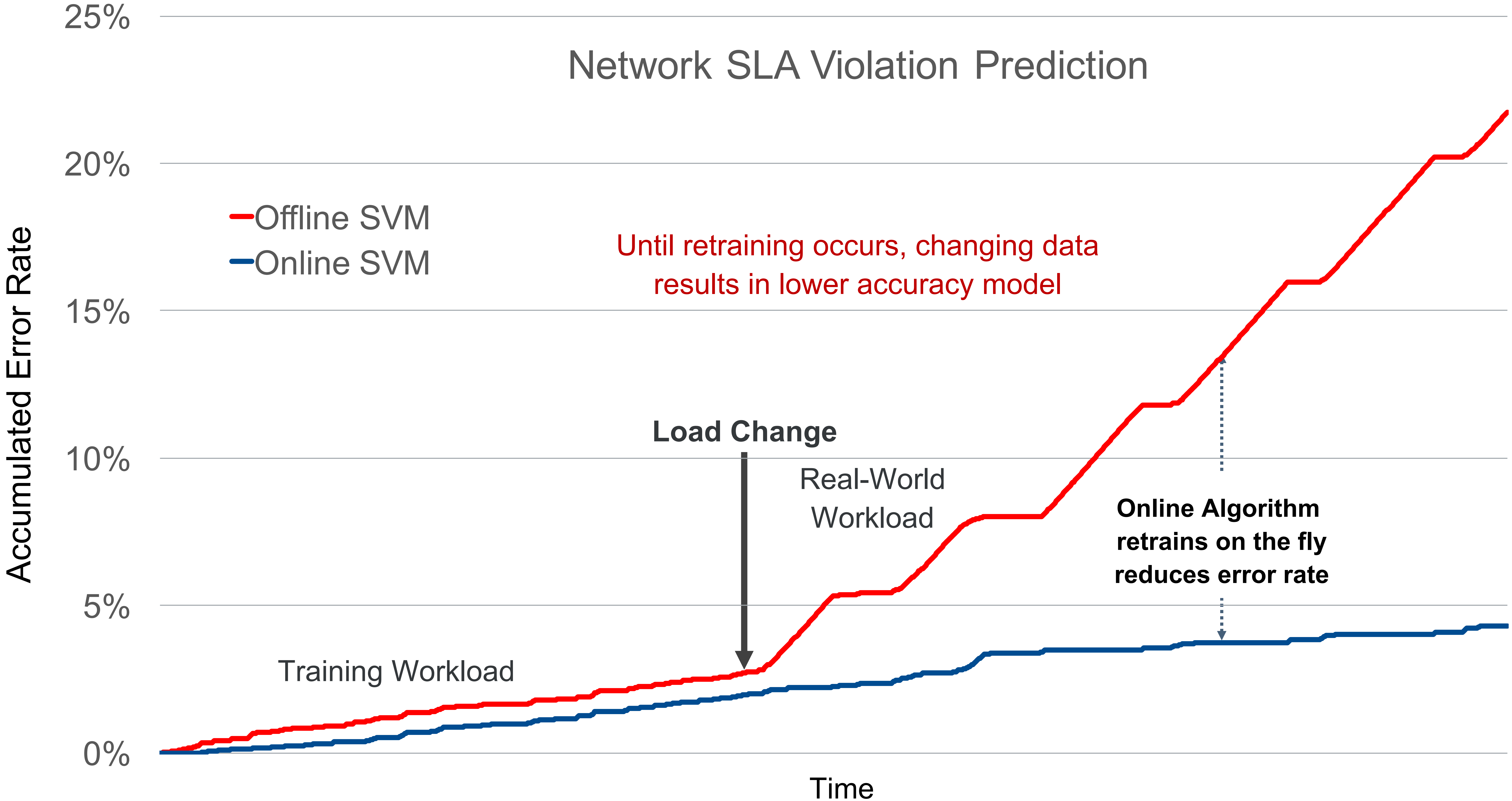
- Load patterns – Flashcrowd, Periodic
- Delivered to Flink and Spark as live stream in experiments

Fixed workloads – Online vs Offline (Batch)

Load Scenario	Offline (LibSVM) Accuracy	Offline (Pegasos) Accuracy	Online SVM Accuracy
flashcrowd_load	0.843	0.915	**0.943**
periodic_load	0.788	0.867	**0.927**
constant_load	0.999	0.999	**0.999**
poisson_load	0.963	0.963	**0.971**

When load pattern remains static (unchanged),
Online algorithms can be as accurate as Offline algorithms

Online SVM vs Batch (Offline) SVM – both in Flink



Online algorithms quickly adapt to workload changes

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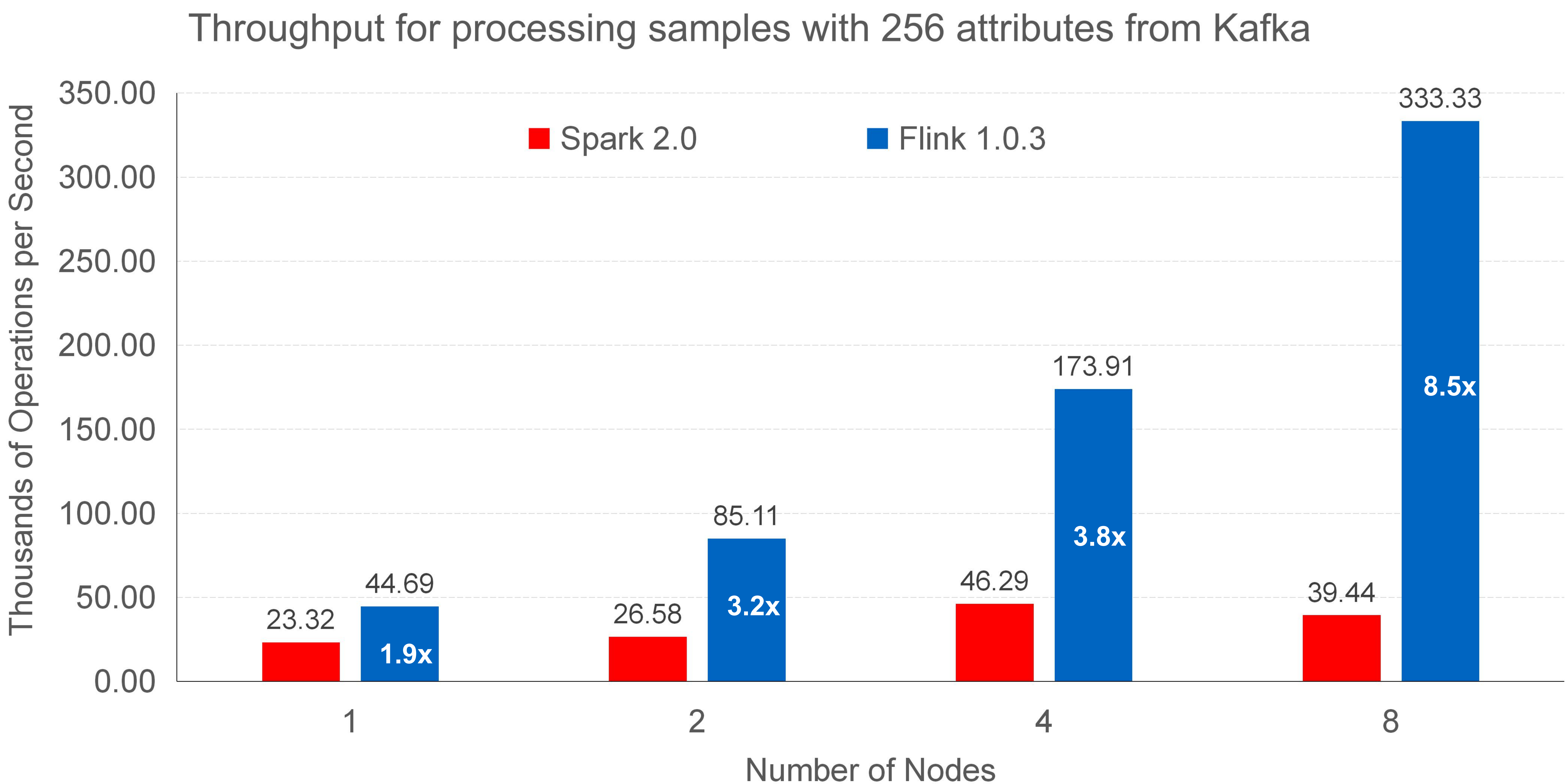
Throughput: Online SVM in Streams and Micro-Batch



Notable performance improvement over micro-batch based solution

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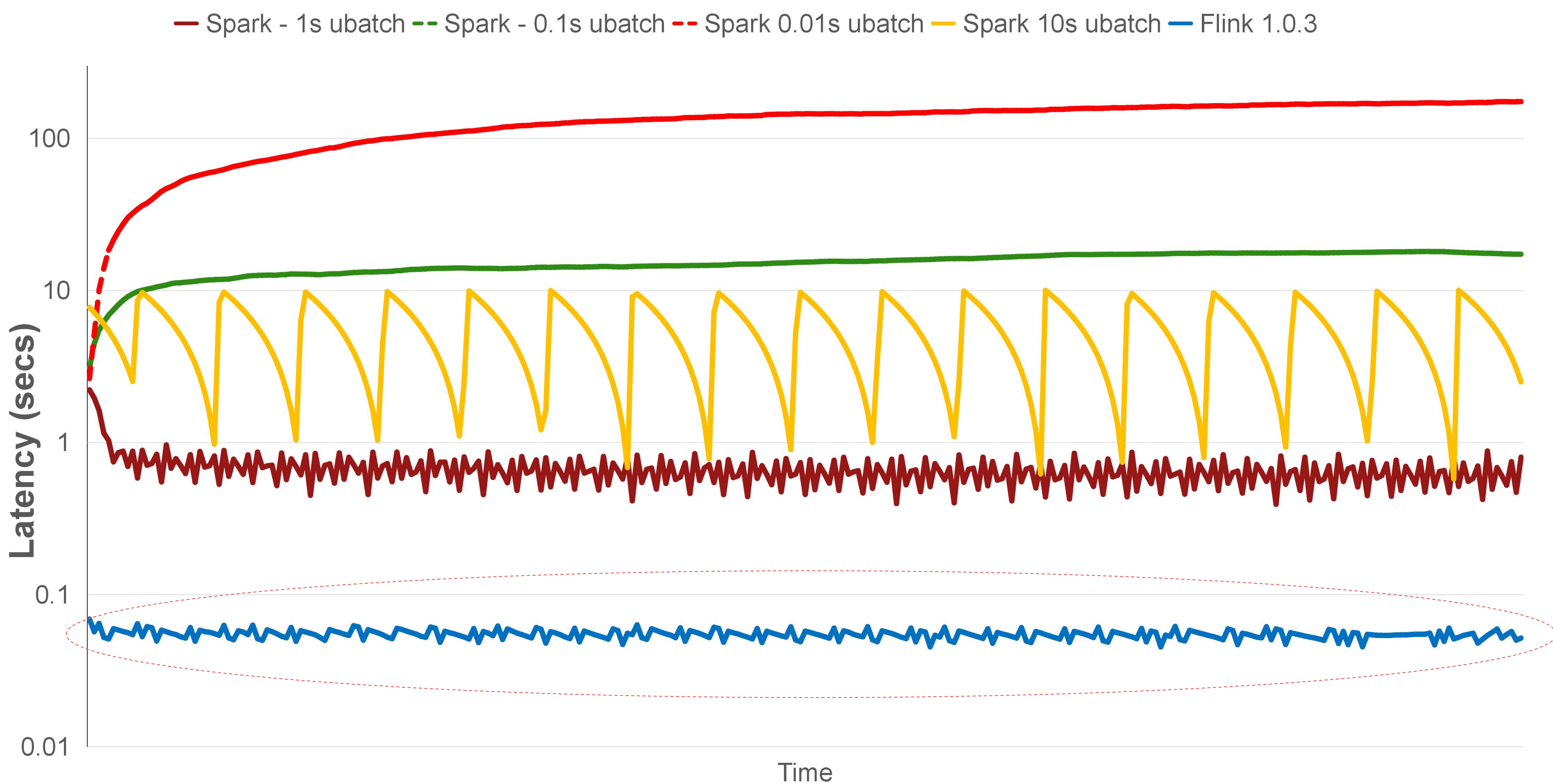
Latency: Online SVM in Streams & Micro-batch



Low and predictable latency as needed in Edge

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Conclusions

Edge computing & Online learning are needed for real-time analytics

- **Edge Computing:** minimizes the excessive latencies, reaction time
- **Online learning:** can dynamically adapt to changing data / behavior

Online machine learning with streaming on Flink

- Supports *low latency processing* with *scaling* across multiple nodes
- Using real world data, demonstrate improved accuracy over offline algorithms

Parallel Machines
The Machine Learning Management Solution

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