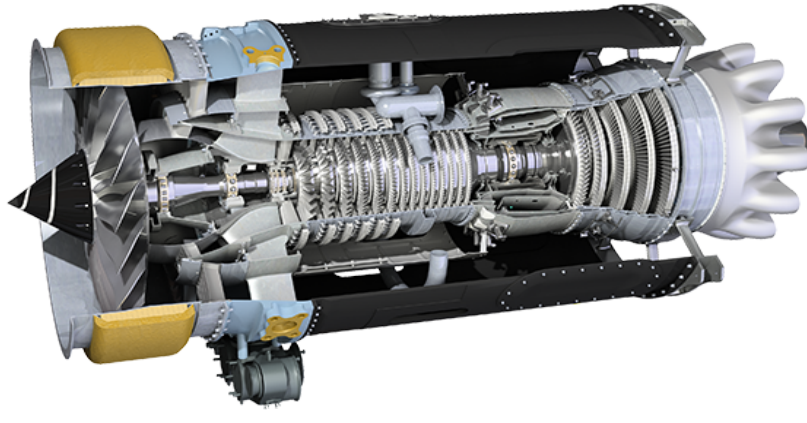


Scalable Architecture for Anomaly Detection and Visualization in Power Generating Assets

Paras Jain, **Chirag Tailor**, Sam Ford, Liexiao (Richard) Ding, Michael Phillips,
Fang (Cherry) Liu, Nagi Gabraeel, Polo Chau

Background



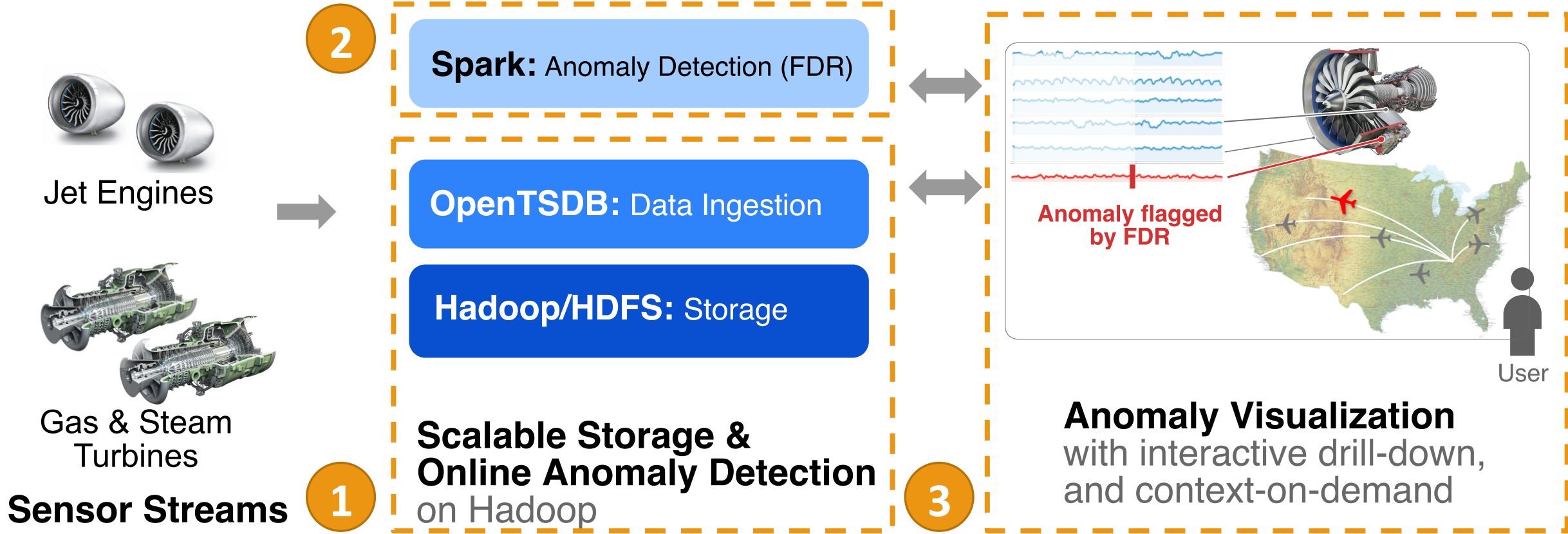
Power generating assets such as jet engines and gas turbines

- Each unit instrumented with 1000s of sensors to signal incipient faults
- Difficult for humans to monitor
- Algorithms attempt to predict asset failure by detecting anomalies

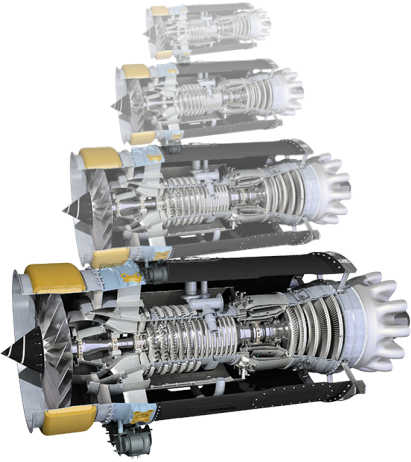
Key Challenges

- ❖ **Storage and Ingestion.** Huge volume of data from many machines in real-time.
- ❖ **Anomaly Detection.** Prevalence of false alarms leads to unnecessary downtime and maintenance.
- ❖ **Visualization.** Lack of an integrated visualization platform to understand and analyze flagged anomalies.

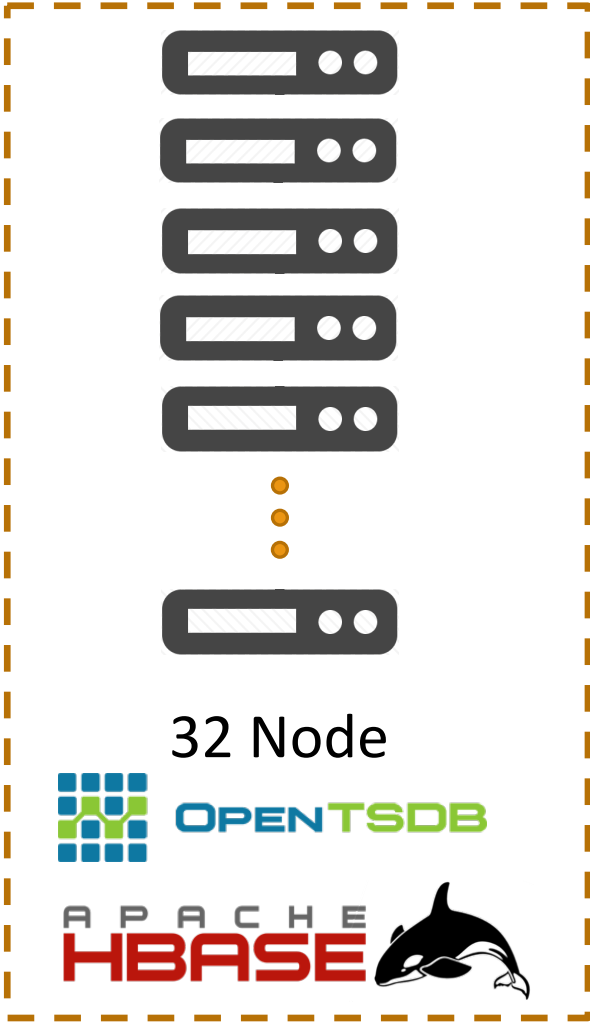
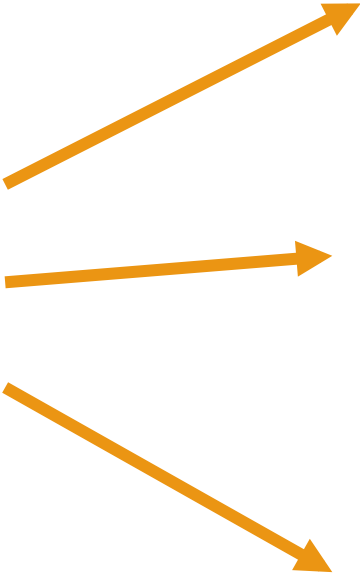
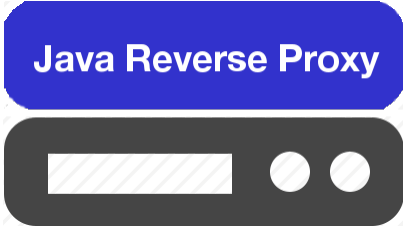
System Overview



1 - Scalable Data Ingestion & Storage Architecture



100 Units
x 1000 Sensors
@ 1HZ



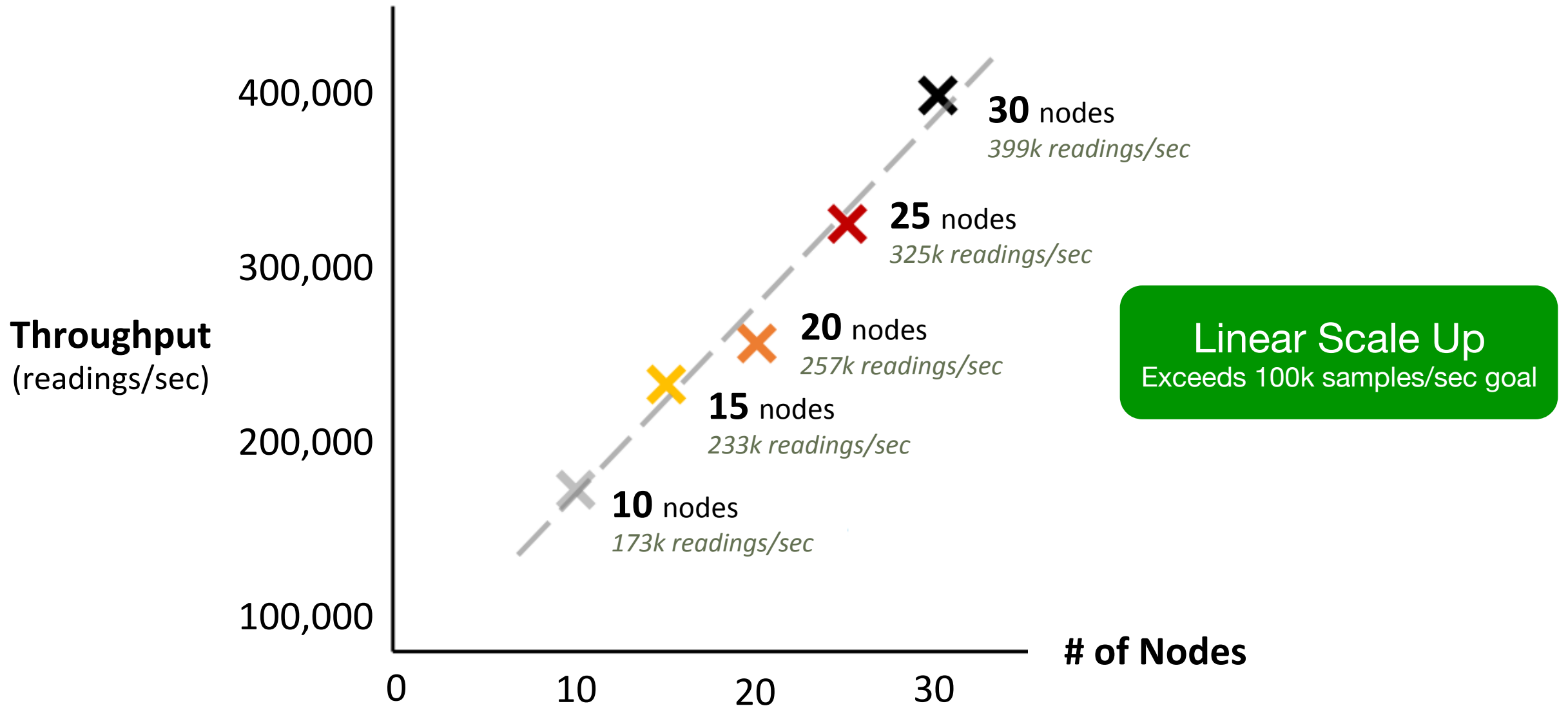
Goal Ingestion Rate: **100,000 sensor readings per second**

1 – Simulated Training Dataset

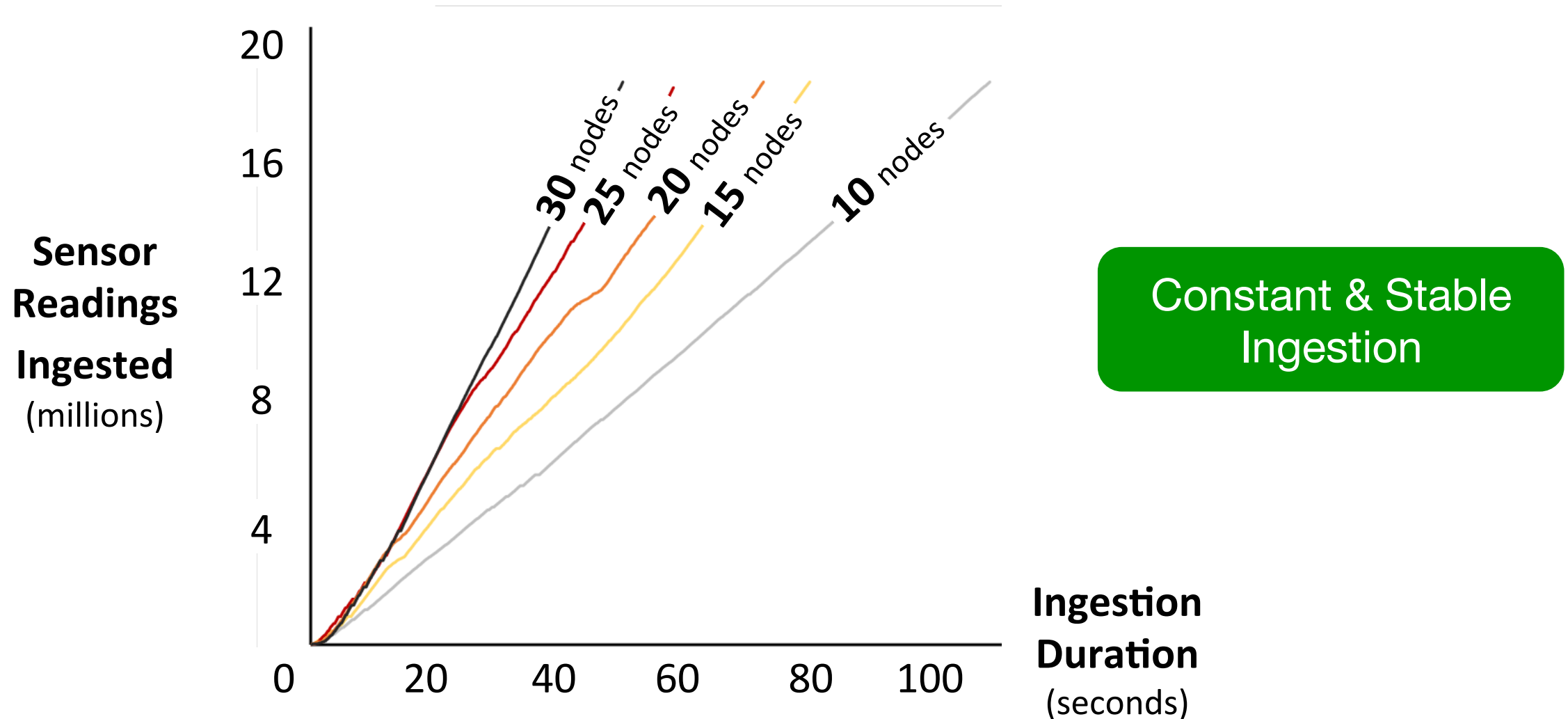
- ❖ **100 units with 1000 sensors producing readings at 1Hz.**
 - Similar number of units owned by a regional energy provider.
 - On the order with 3000 sensors in Siemens SGT5-8000H gas turbine*.
- ❖ **Anomalous behavior modeled in dataset:**
 - Pure random noise.
 - Pure random noise plus gradual degradation.
 - Pure random noise plus sharp shift.

*P. Ratliff, P. Garbett, and W. Fischer, “The new siemens gas turbine sgt5-8000h for more customer benefit,”

1 - Scalable Data Ingestion & Storage Results



1 - Scalable Data Ingestion & Storage Results



1 - Interesting Findings

- 1. Salting.** HBase keys generated by OpenTSDB must be salted since continuous value timestamps all map to the same HBase node.
- 2. Backpressure.** HBase does not provide backpressure to OpenTSDB.



OPENTSDDB

A P A C H E
HBASE



2 - Flagging Anomalies with Low False Alarm Rates

We use the **False Discovery Rate** (FDR) algorithm.

1. First introduced by **Benjamini and Hochberg in 1995** and used in multiple inference clinical trials*.
2. **Suppresses false alarms:** Performs a test on an increasing ratio of the original significance level for each sensor's z-score.
3. **Scalable:** our implementation using Spark processes over **939,000 sensor samples per second**

*Y. Benjamini and Y. Hochberg, "Controlling the false discovery rate: a practical and powerful approach to multiple testing,"

3 - Anomaly Visualization



Machines

- Machine 10
- Machine 11
- ✖ Machine 12
- Machine 13
- Machine 14
- Machine 15
- ✖ Machine 16
- Machine 17
- Machine 18
- Machine 19
- ✖ Machine 20

1

Machine 17

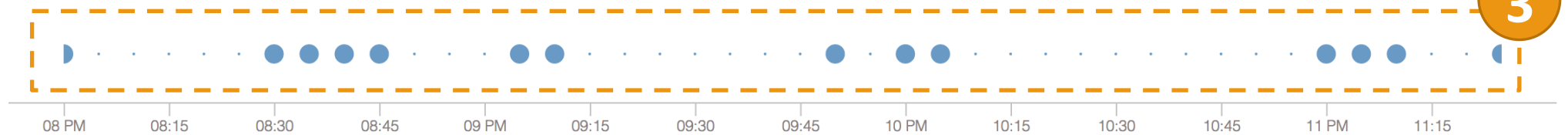
Anomalous

All

x 0 x 2 x 4 x 5 x 9

2

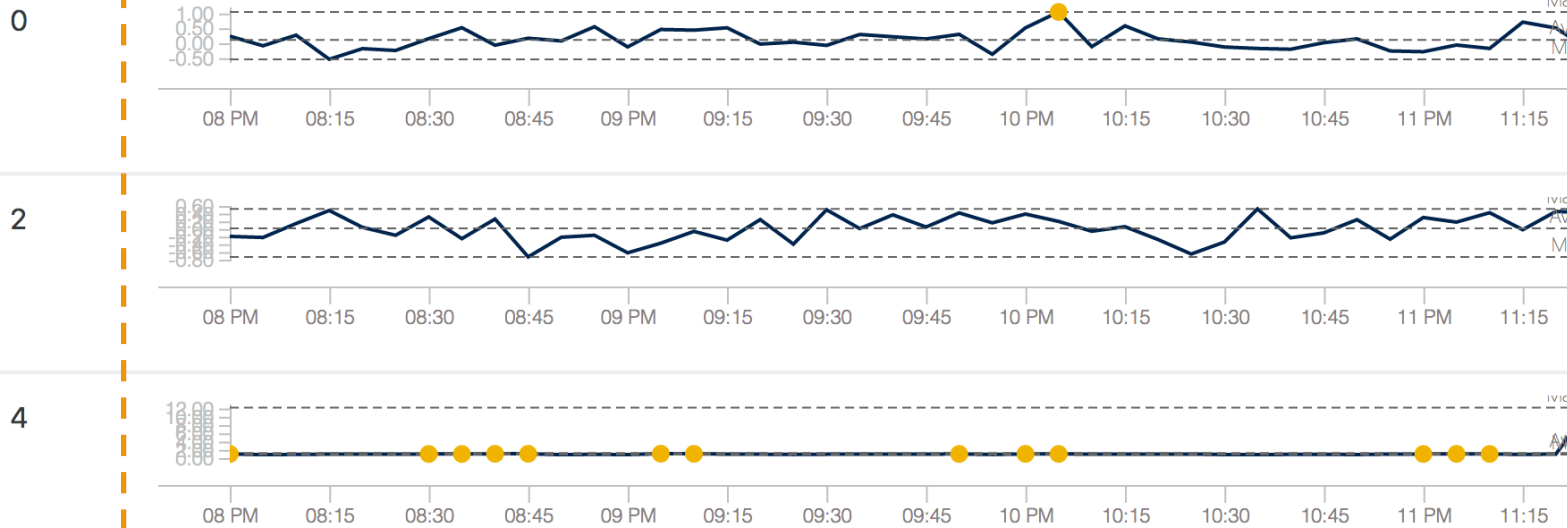
Number of anomalies in last 30 days: 14



3

Sensor

Daily Sparkline



4

Value Change

0.238 1.892%

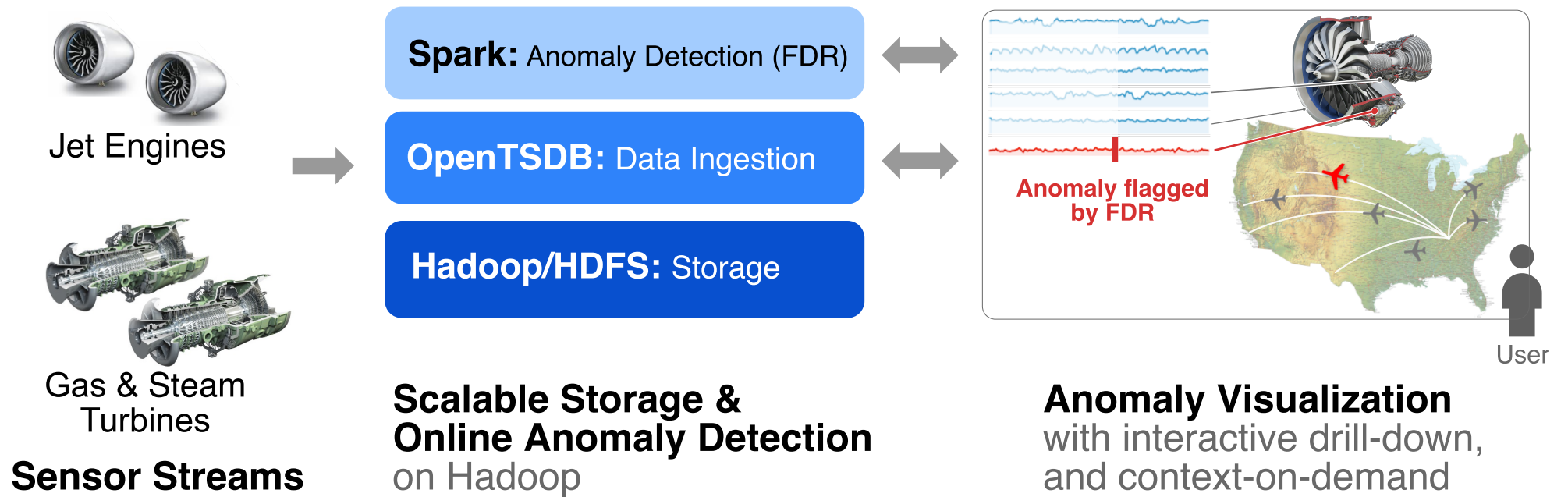
-0.193 3.172%

-- -11.038%

Ongoing Work

- Scaling up ingestion and analysis throughput with additional nodes.
- Migrate anomaly detection algorithm to Spark Streaming for online evaluation.
- Evaluate our system with domain users and industry partners like General Electric (GE).

Thanks!



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