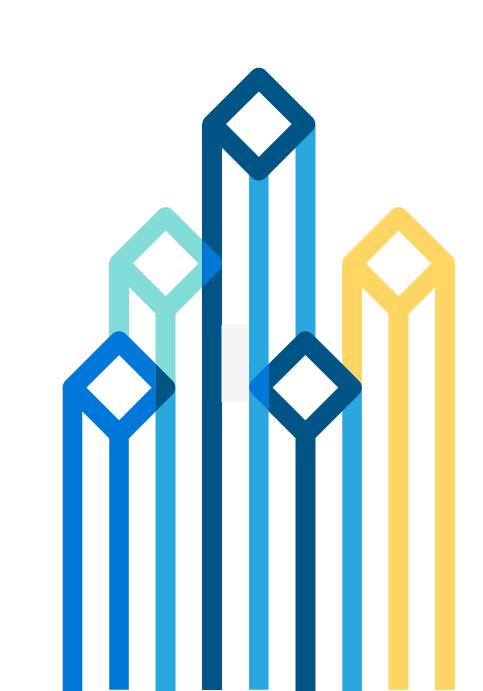
cloudera[®]

Modern Historian Data Analytics

Samir Gupta, Sales Engineer **Sheridan McDonald**, Account Executive January, 2017



Existing Historian Architecture



On-shore Well



Off-shore Well



Regional Historian Server





Challenges with Existing Architecture

- Expensive
- Proprietary technology
 - Limited analytics capabilities
 - No inherent relationships between data and tags
 - Difficult to get data out in a useful format ie. by individual tag ID
 - Ancient historian tooling to analyze the data
- No real-time access to the data
 - Raw data needs processing to be easily visualized
- Not well integrated with the data management ecosystem
 - Need to analyze in Excel, which as a 1M record limit (<.001% of data)



Modern Historian Architecture



On-shore Well

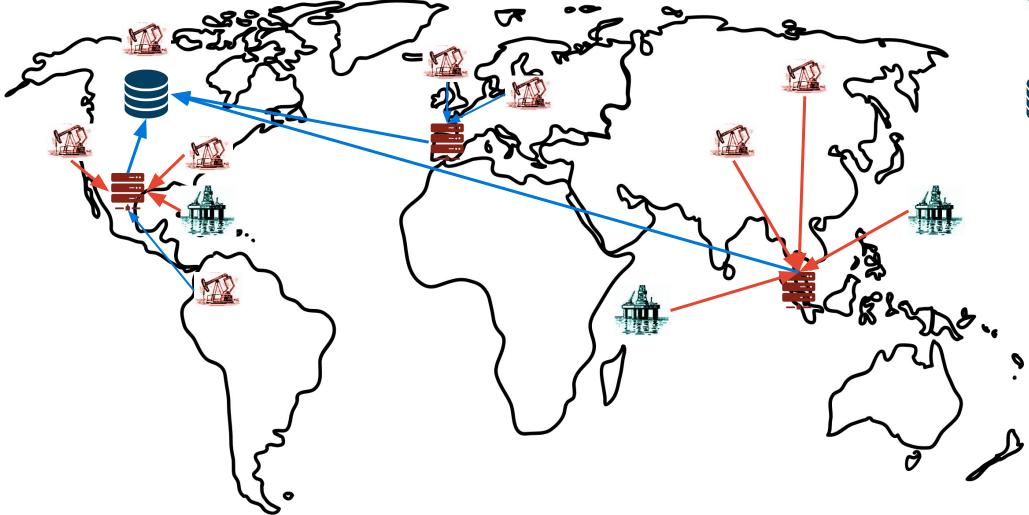


Off-shore Well



Regional Historian Server





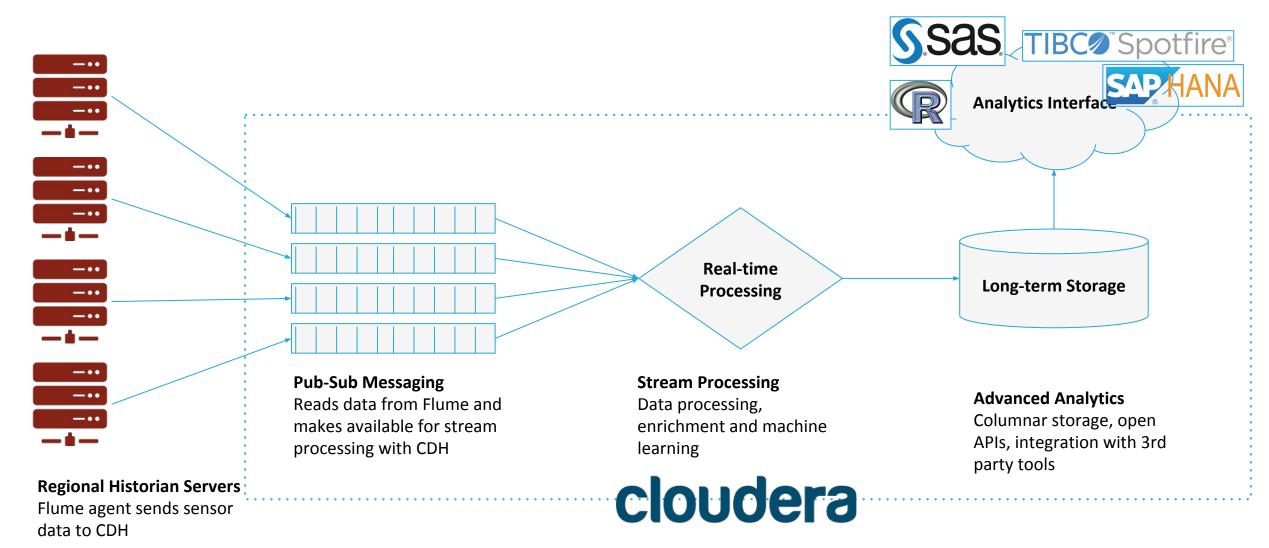


Benefits with Modern Architecture

- Cost Effective
- Open technology
 - Advanced analytics capabilities
 - Easily create relationships between raw data and tag information
 - Integrate with any analytic tooling
- Real-time access to the data
 - Real-time processing of data
- Analyze all sensor data, instead of a small subset
 - 100B+ rows vs. 1M

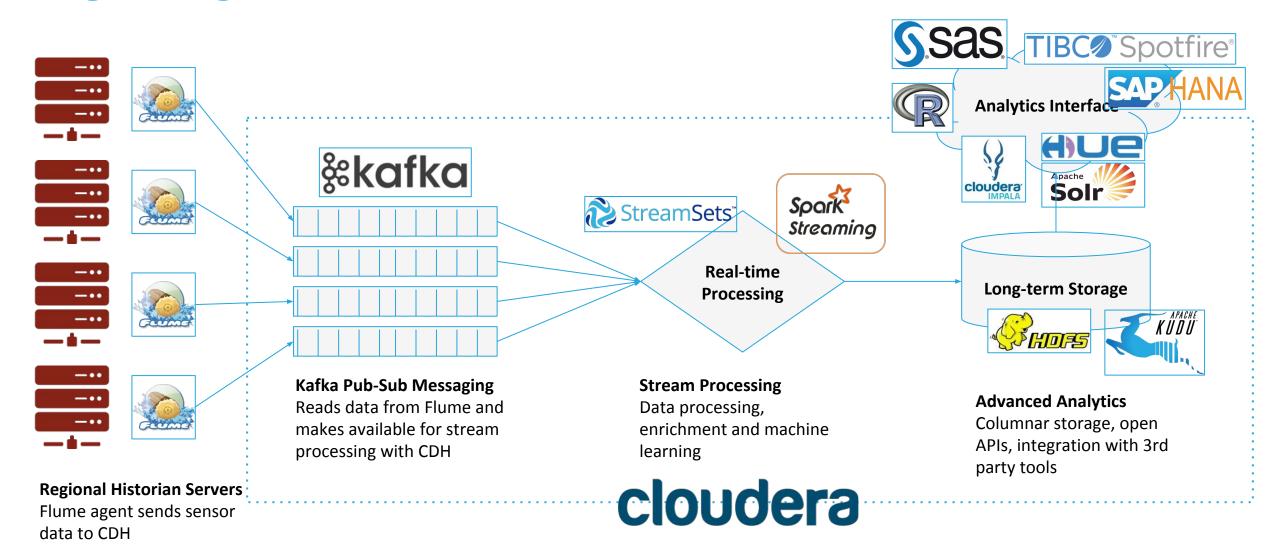


Ingesting PHD Data into Cloudera



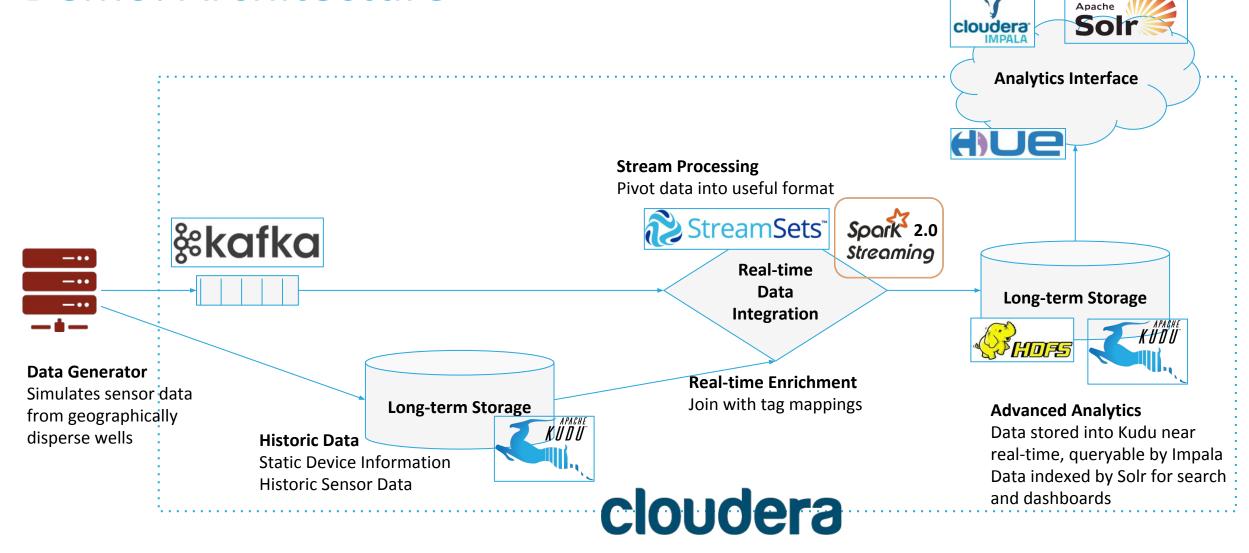


Ingesting Historian Data into Cloudera



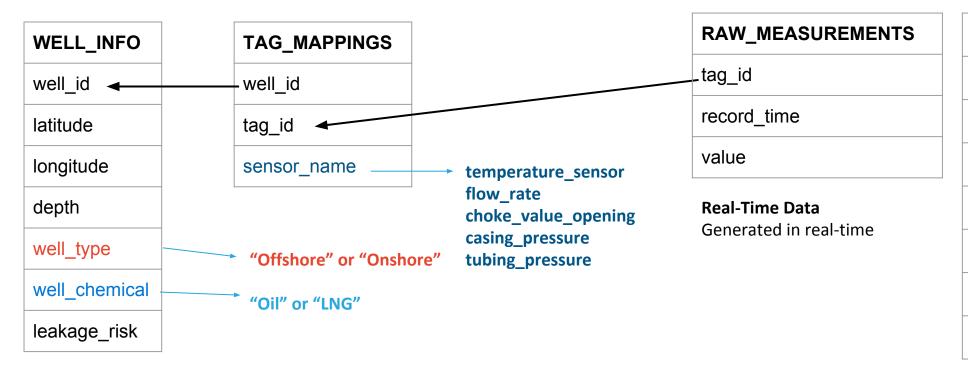


Demo: Architecture





Demo: Data Model



MEASUREMENTS

well_id

record_time

temperature_sensor

flow_rate

choke_value_opening

casing_pressure

tubing_pressure

Static Data

Generated during initial setup, configurable Stored in Impala using KUDU for fast lookup

Real-Time Data

Enriched in real-time with Spark Evaluator in Streamsets Stored in near-real-time into KUDU



Demo: Pivot in Spark

tag_id	record_time	value
1	9:00:00	50
2	9:00:00	12
3	9:00:00	80
1	9:00:30	48
2	9:00:30	14

tag_id	record_time	value	well	sensor_name
1	9:00:00	50	1	temp_sensor
2	9:00:00	12	1	flow_rate
3	9:00:00	80	1	casing_pressu re
1	9:00:30	48	1	temp_sensor
2	9:00:30	14	1	flow_rate
3	NULL	NULL	NULL	pressure

well_id	record_time	temp	flow	pressure
1	9:00:00	50	12	80
1	9:00:30	48	15	NULL

PIVOT ON sensor_name

UPSERT INTO KUDU

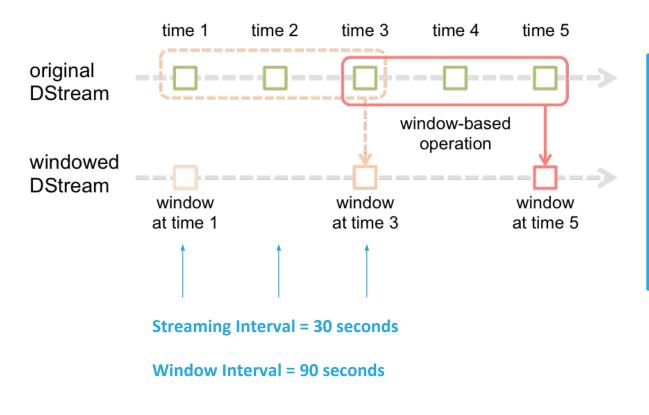


tag_id	weii_ia	sensor_name	
1	1	temp	
2	1	flow	
3	1	pressure	

RAW_MEASUREMENTS
OUTER JOIN
TAG_MAPPINGS
ON tag_id



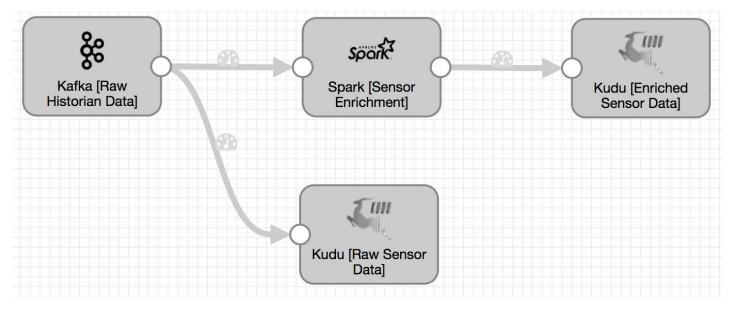
Demo: Spark Streaming Windows



well_id	record_time	pressure	
1	9:00:00	50	
2	9:00:00	80	
1	9:00:30	52	
2	9:00:30	NULL at W1, 81 at W2	
1	9:01:00	49	1
2	9:01:00	76	Window 1
1	9:01:30	55	
2	9:01:30	86	Window 2
1	9:02:00	50	
2	9:02:00	NULL	Window 3



Demo: Streamsets Data Collector



Kudu Table

Sends enriched sensor data to Impala table to be queried and used in BI

Kafka Source

Reads raw sensor data from Kafka cluster

Custom Spark Evaluator

enrich sensor data Pivot and aggregate before sending to Kudu

Kudu Table

Real-time lookup to Kudu to Raw sensor data also stored in Kudu for post-processing analysis/debug

Streamsets running in "Cluster Mode" to read directly from a Kafka cluster. The entire pipeline will run as a **Spark streaming application inside CDH.**





cloudera

Thank you samir Gupta, Systems Engineer sgupta@cloudera.com

Sheridan McDonald smcdonald@cloudera.com