

Overview of Big Data Solutions and Services at CERN

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CERN Knowledge Transfer Forum meeting
CERN, September 29th, 2017

Data at scale @CERN

- **Physics** data – we use WLCG to handle it
 - Optimised for physics analysis and concurrent access
 - ROOT framework - custom software and data format
- **Infrastructure** data and metadata
 - Accelerators and detector controllers
 - Data catalogues (collisions, files etc)
 - Monitoring of the WLCG and CERN data centres
 - Systems logs

Modern Distributed Systems for Data Processing

- Tools from industry and open source
 - “Big Data”
 - Distributed systems for data processing
 - Can operate a scale
 - Typically on clusters of commodity-type servers/cloud
 - Many solutions target data **analytics** and data warehousing
 - Can do much more: data ingestion, **streaming**, **machine learning**

Declarative Interfaces for Parallelism

- Young technology but already evolved
 - It is not about SQL vs. no SQL, Map-Reduce
 - SQL is still strong (+ not only SQL, functional languages, etc)
- Systems for data analytics deploy **declarative** interfaces
 - Tell the system what you want to do
 - Processing is transformed into graph (DAG) and **optimized**
 - Execution has to be fault-tolerant and distributed

Data Engines on Hadoop Ecosystem

- Several solutions available
 - Pick your data engines and storage formats
- **Data-analytics** and data warehouse
 - Hadoop / “Big Data Platforms” are often the preferred solution
 - Cost/performance and scalability are very good
- Online systems
 - Competition still open with RDBMS and new in-memory DBs
 - Added value: build platforms to do both online + analytics

Hadoop Ecosystem – The Technology

- Hadoop clusters: **YARN** and **HDFS**
- Notable components in the ecosystem
 - **Spark, HBase**, Map Reduce
 - Next generation: Kudu
- Data ingestion pipelines
 - **Kafka**, Spark streaming

Managed **Services** for Data Engineering

- **Platform**
 - Capacity planning and configuration
 - Define, configure and support components
- Running central **services**
 - Build a team with domain expertise
 - Share experience
 - Economy of scale

Hadoop Service at CERN IT

- Setup and run the infrastructure
- Provide consultancy
- Support user community
- Running for more than 2 years

Collaboration Services

- ✔ Conference Rooms
- ✔ E-Mail
- ✔ Eduroam
- ✔ Lync
- ✔ Sharepoint

Computer Security

- ✔ Certificate
- ✔ Single Sign

Data Analytics

- ✔ **HADOOP**

Database Services

- ✔ Accelerato
- ✔ Administra
- ✔ Database
- ✔ Database
- ✔ Experimen
- ✔ General Pu

Desktop Services

- ✔ Linux Desktop
- ✔ Windows Desktop

- ✔ Electronics D
- ✔ Mathematics

Normal since: 31 Aug 2015 11:21

[Link to availability history](#)

Details:

Cluster: Hadalytic (overall availability: 100)

HDFS - Availability: 100

YARN - Availability: 100

Spark - Availability: 100

HBase - Availability: 100

Hive - Availability: 100

Impala - Availability: 100

Cluster: LXHadoop (overall availability: 100)

HDFS - Availability: 100

YARN - Availability: 100

Hive - Availability: 100

Cluster: Analytix (overall availability: 100)

HDFS - Availability: 100

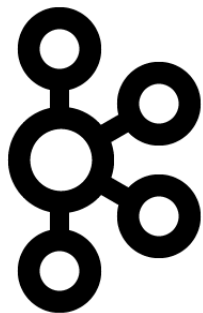
YARN - Availability: 100

Spark - Availability: 100

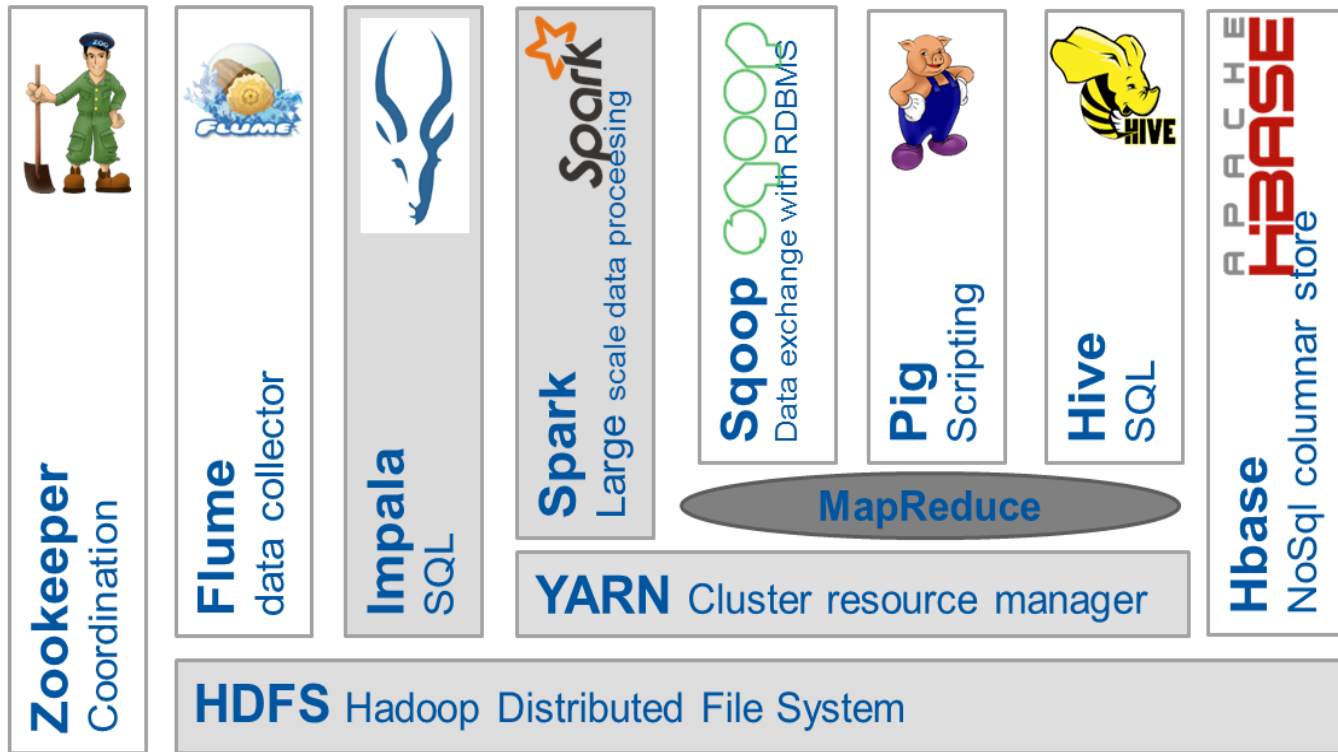
Hive - Availability: 100

- ✔ Load Balanci
- ✔ Messaging

Overview of Available Components



Kafka:
streaming
and ingestion



Hadoop Clusters at CERN IT

- 3 current production clusters (+ 1 for QA)
- A new system for **BE NXCALS** (accelerator logging) platform
 - Coming in Q4 2017

Cluster Name	Configuration	Primary Usage
lxhadoop	18 nodes (cores – 576,Mem – 1.15TB,Storage – 1.17 PB)	Experiment activities
analytix	36 nodes (cores – 780,Mem – 2.62TB,Storage – 3.6 PB)	General Purpose
hadalytic	12 nodes (cores – 384,Mem – 768GB,Storage – 2.15 PB)	SQL oriented installation
NxCALS	24 nodes (cores – 1152,Mem – 12TB,Storage – 4.6 PB, SSD - 92 TB)	Accelerator Logging Service

Data volume (from backup stats July2017)

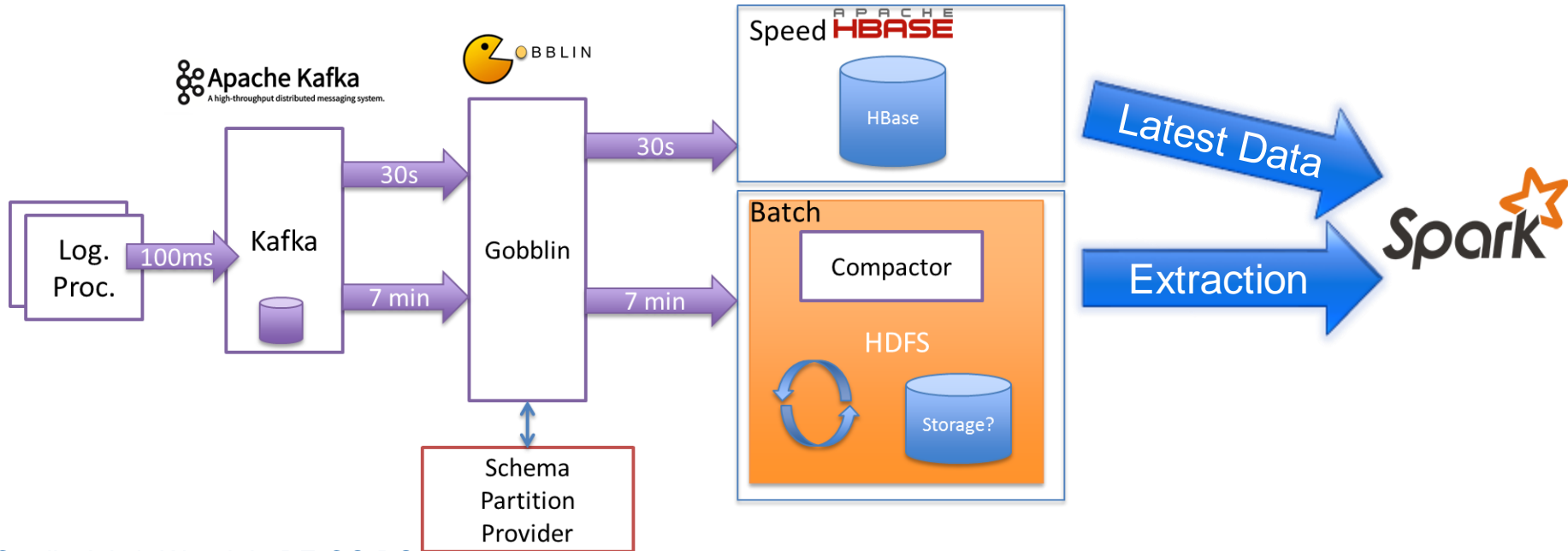
Application	Current Size	Daily Growth
IT Monitoring	420.5 TB	140 GB
IT Security	125.0 TB	2048 GB
NxCALS	10.0 TB	500 GB
ATLAS Rucio	125.0 TB	~200 GB
AWG	90.0 TB	~10 GB
CASTOR Logs	163.1 TB	~50 GB
WinCC OA	10.0 TB	25 GB
ATLAS EventIndex	250.0 TB	200 GB
USER HOME	150.0 TB	20 GB
Total	1.5 PB	4 TB

Highlights and Use Cases

- Accelerator logging
- Industrial controls
- Streaming, data enrichment, analytics
 - Monitoring team
 - Security team
- Physics
 - Development of “Big Data solutions” for physics
 - Analytics, for experiments computing

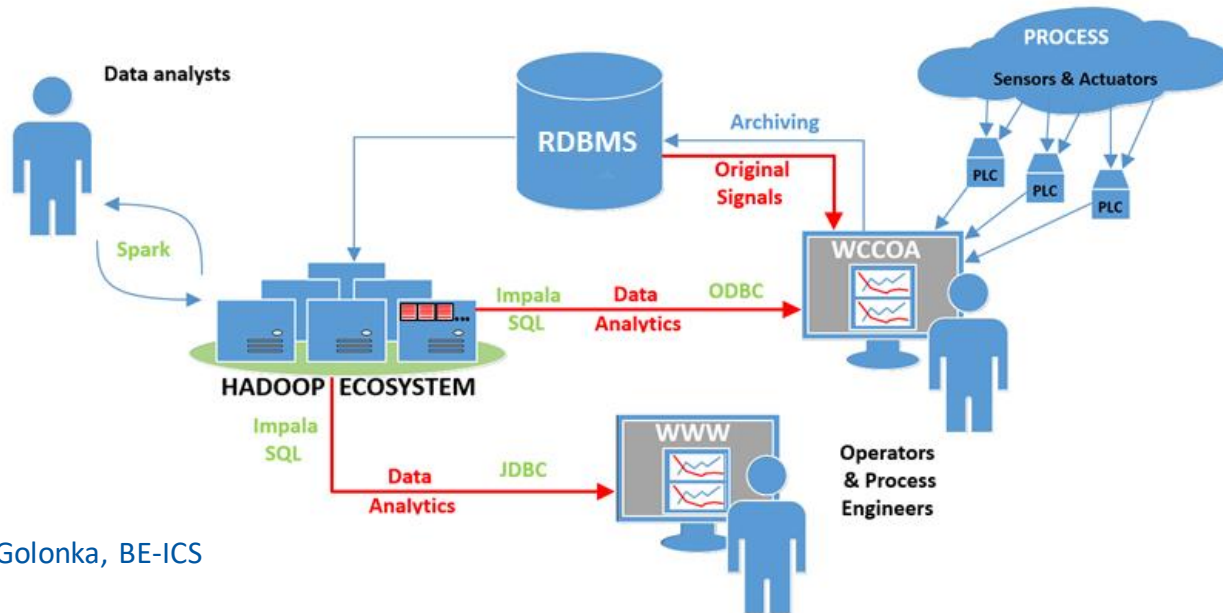
Next Gen. Archiver for Accelerator Logs

Pilot architecture tested by CERN Accelerator Logging Services
Critical system for running LHC - 700 TB today, growing 200 TB/year
Challenge: service level for critical production



Industrial control systems

- Complex monitoring and metric archiving of devices in the LHC tunnel and detectors
 - Current data rates: 250kHz, 500GB/day

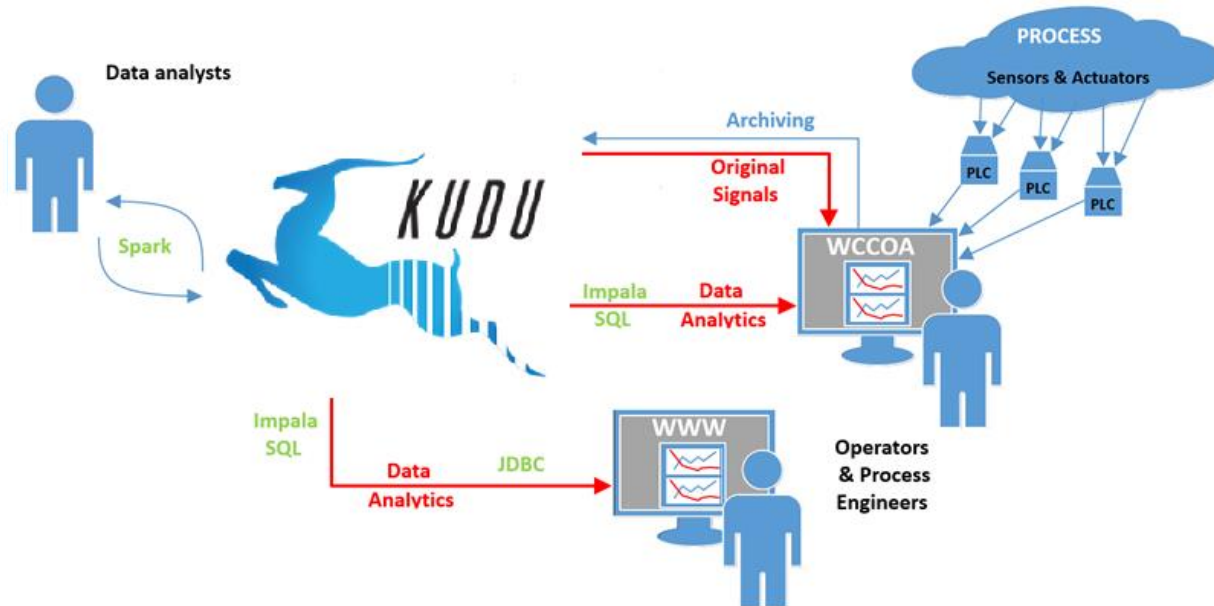


Credit: Piotr Golonka, BE-ICS

Possible Evolution - SCADA controls

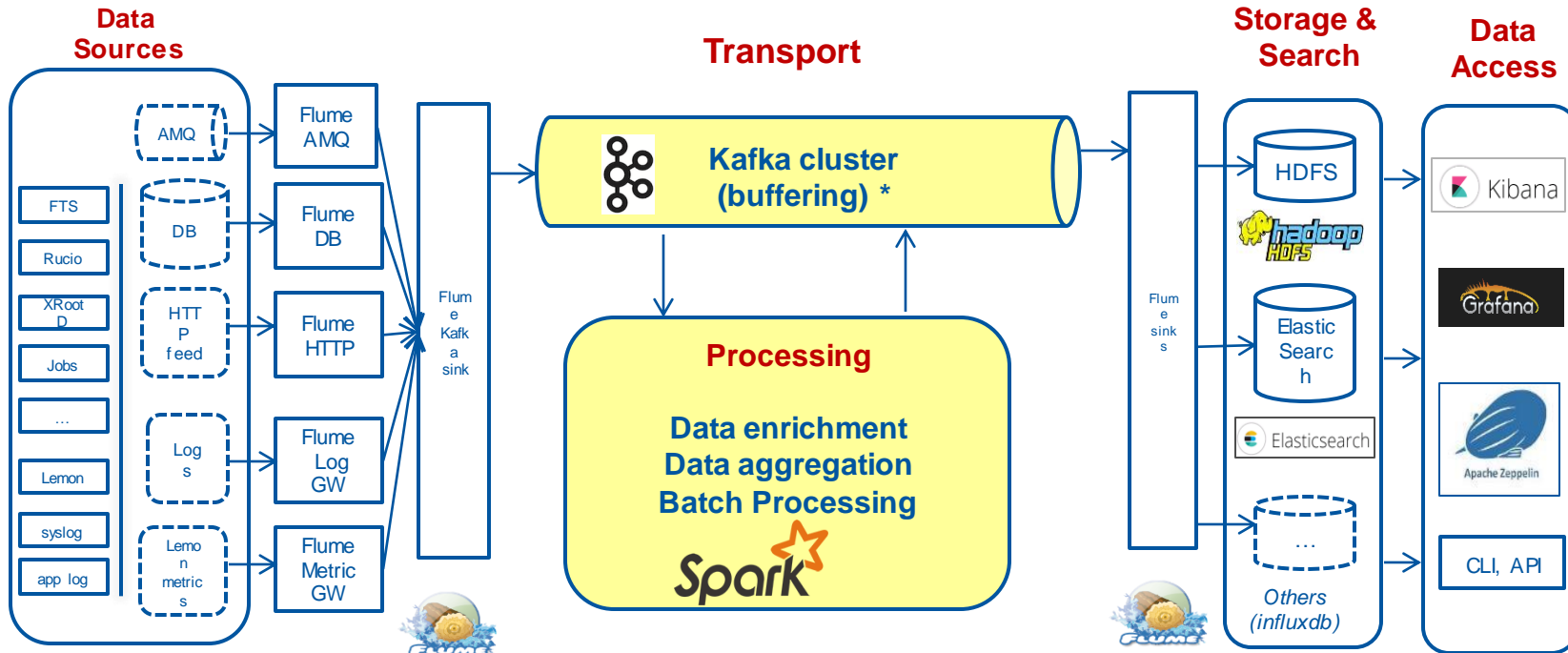
What can we gain with Kudu:

- reduce ingestion latency for analytics
- speed up live data queries and reporting
- simplification of the system



New IT Monitoring

Critical for CC operations and WLCG

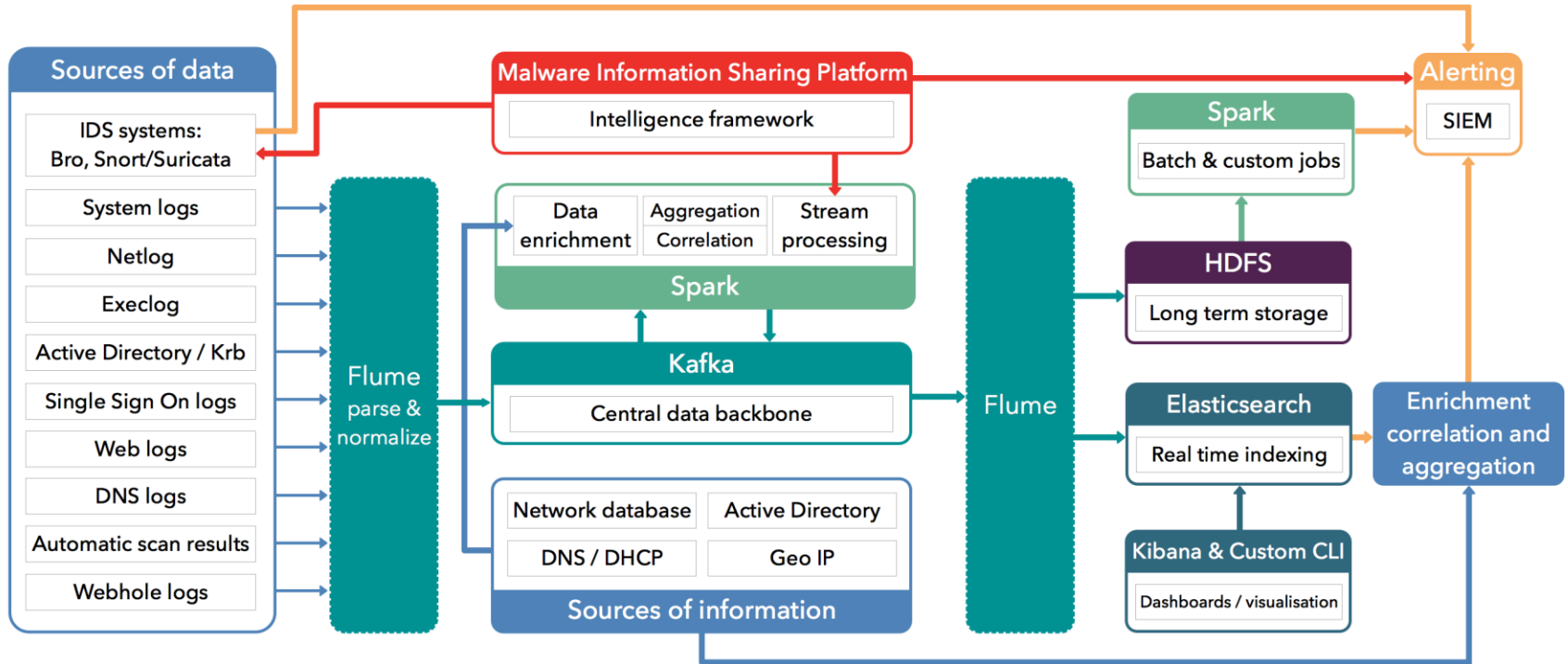


- Data now 200 GB/day, 200M events/day
- At scale 500 GB/day
- Proved effective in several occasions



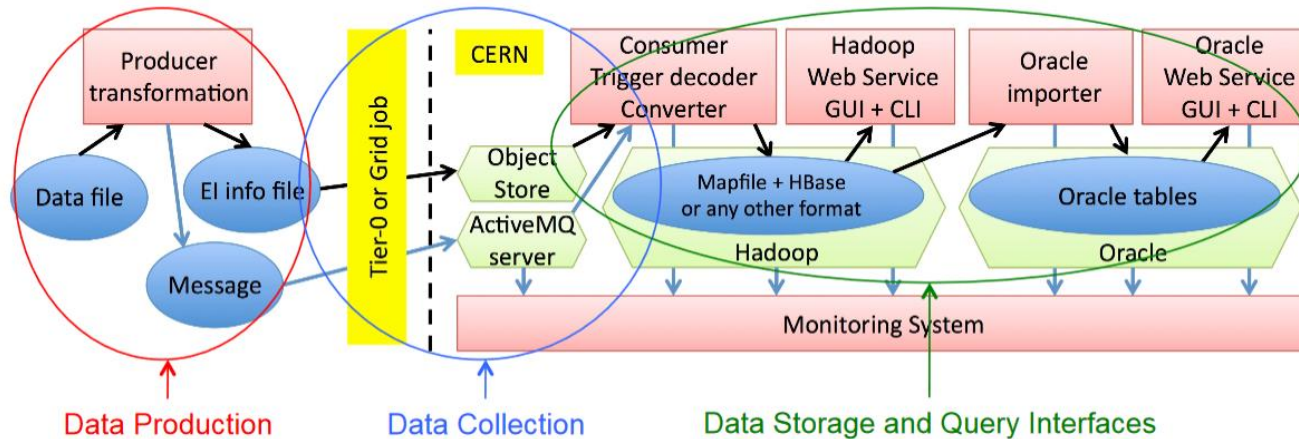
Computer Security

intrusion detection use cases



ATLAS EventIndex

- Searchable catalog of ATLAS events
 - First “Big Data” project in our systems
 - Over 80 billions of records, 140TB of data

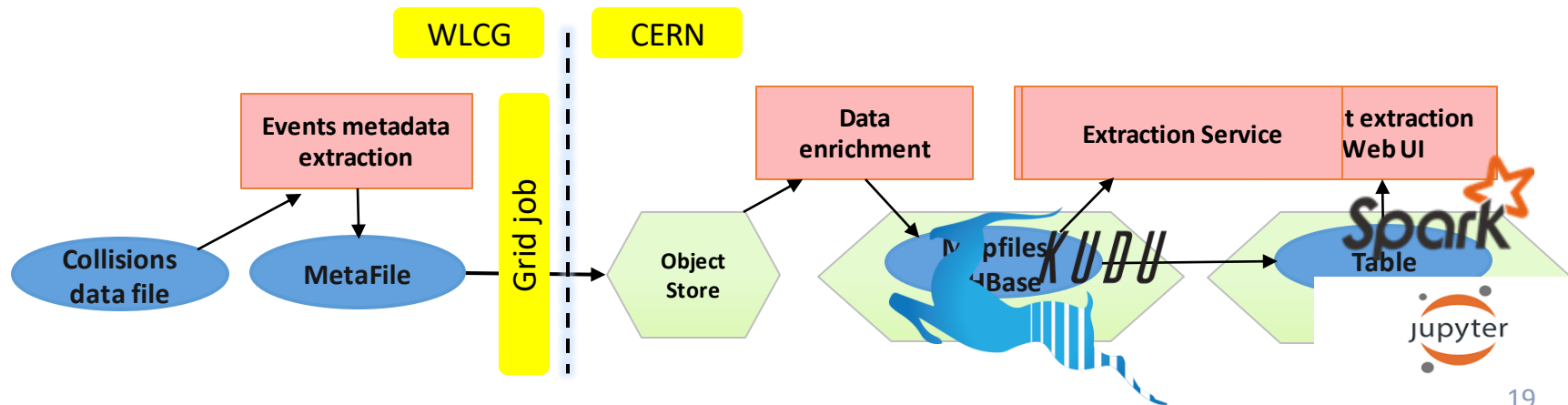


Credits: Dario Barberis, 2017

Possible evolution -> ATLAS EventIndex

What can we gain with Kudu:

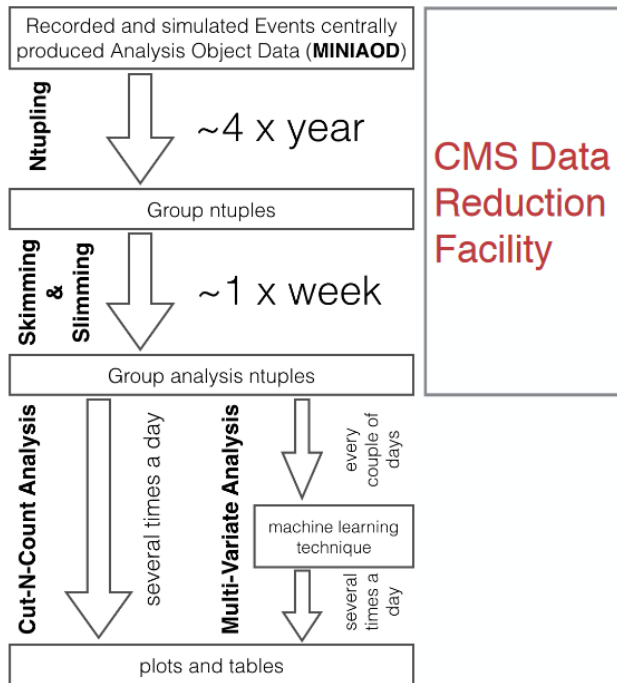
- Reduce ingestion latency by removal of multi-staged data loading into HDFS
- Enable in place data mutation
- Enable common analytic interfaces Spark and Impala
- ...and increase analytic performance



CMS Big Data Project and Openlab



Proposal: CMS Data Reduction Facility



- Demonstration facility optimized to read through petabyte sized storage volumes
 - Produce sample of reduced data based on potentially complicated user queries
 - Time scale of hours and not weeks
- If successful, this type of facility could be a big shift in how effort and time is used in physics analysis
 - Same infrastructure and techniques should be applicable to many sciences

Physics Analysis and “Big Data” ecosystem

- Challenges and goals:
 - Use tools from industry and open source
 - Current status: Physics uses HEP-specific tools
 - Scale of the problem 100s of PB – towards **exascale**
 - Develop interfaces and tools
 - Already developed first prototype to read **ROOT** files into Apache **Spark**
 - Hadoop-XRootD connector -> Spark can read from EOS
 - Challenge: testing at scale

Jupyter Notebooks and Analytics Platforms



- Jupyter notebooks for data analysis
 - System developed at CERN (EP-SFT) based on CERN IT cloud
 - SWAN: Service for Web-based Analysis
 - ROOT and other libraries available
- Integration with Hadoop and Spark service
 - Distributed processing for ROOT analysis
 - Access to EOS and HDFS storage
 - Opens the possibility to do **physics analysis on Spark** using Jupyter notebooks as interface
 - An example notebook with CERN/LHCb **opendata** -> <https://cernbox.cern.ch/index.php/s/98RK9xIU1s9Lf08>

Jupyter Notebooks and Analytics Platforms

Apache Spark

LHCb Opendata

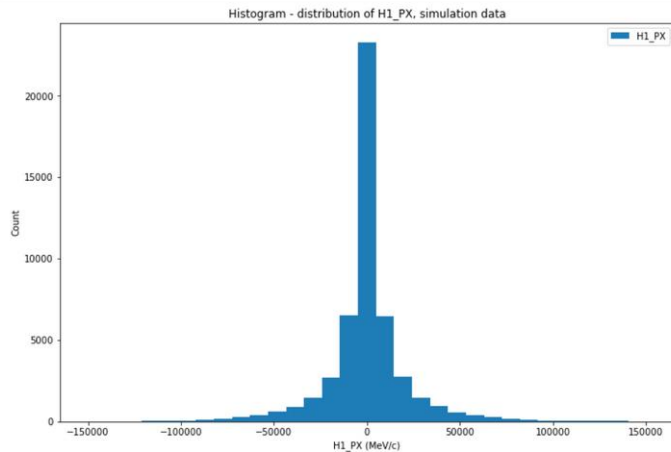
This notebook illustrates a nice interplay between LHCb Opendata, Spark and ROOT - all teaching interesting flavour Physics!

Plotting a feature:

You can plot any feature of the data in a histogram. Choose any suitable binning that allows you to observed the distribution of the variable clearly. We will plot a histogram for the first kaon candidate's momentum x-component (H1_PX):

```
In [8]: # Plot a histogram of the distribution of the H1_PX variable, using Pandas
# This is a basic solution that moves all the data from the Spark DataFrame
# into a Python Pandas DataFrame. It's OK for small data sets, but it has scalability issues

hlpx_data = sim_data_df.select("H1_PX").toPandas() # select H1_PX data and moves it to Pandas
hlpx_data.plot.hist(bins=31, range=[-150000, 150000], title="Histogram - distribution of H1_PX, simulation data")
xlabel('H1_PX (MeV/c)')
ylabel('Count');
```



Open in SWAN



SWAN Customisation

Specify the parameters that will be used to contextualise the container which is created for you. See the [online SWAN guide](#) for more details.

Software stack [more...](#)

Platform [more...](#)

Environment script [more...](#)

Number of cores [more...](#)

Number of cores to associate to the container.

Spark cluster [more...](#)

Start my Session

Jupyter Notebooks and Analytics Platforms



Streaming SQL ML Graph

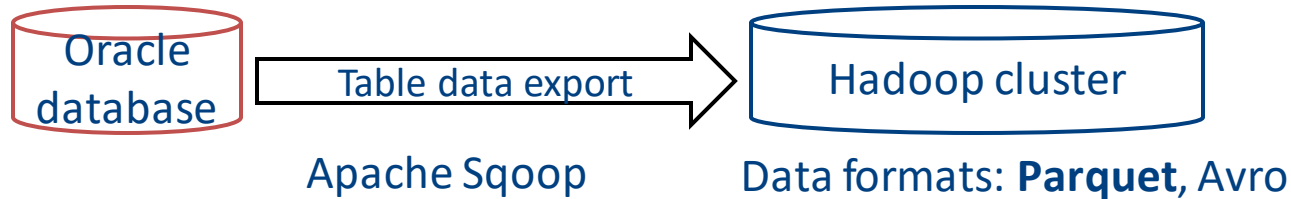


ROOT
Data Analysis Framework

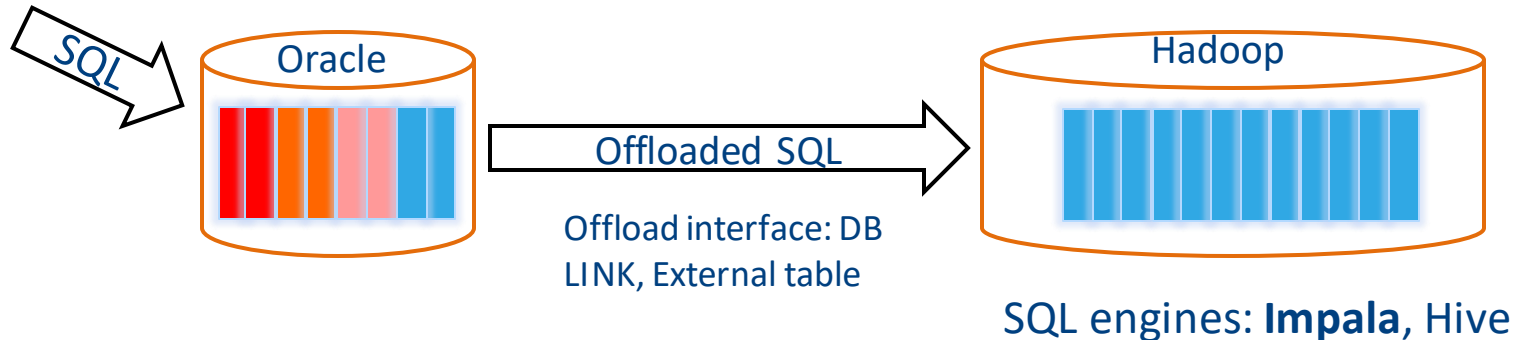


Offloading from Oracle to Hadoop

- Step1: Offload **data** to Hadoop



- Step2: Offload **queries** to Hadoop



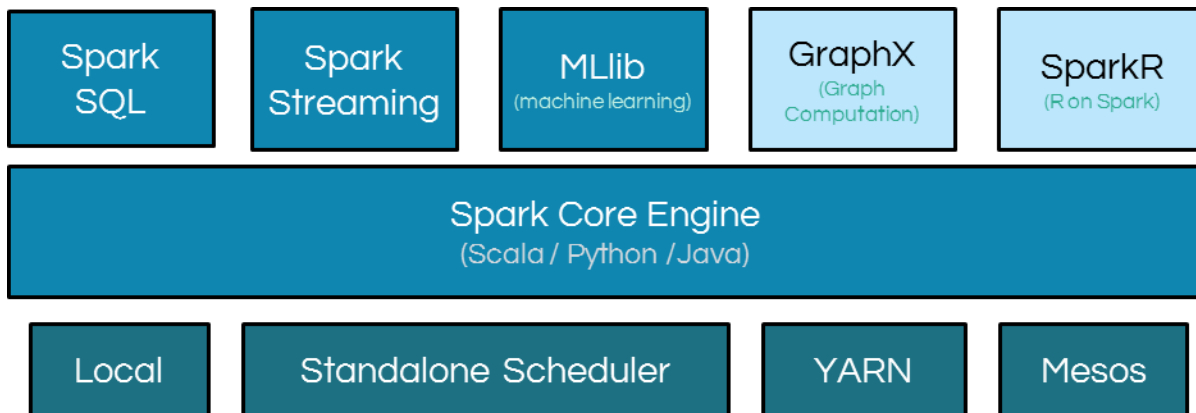
Analytics platform for controls and logging

- Use distributed computing platforms for storing analyzing controls and logging data
 - Scale of the problem 100s of TBs
- Build an analytics platform
 - Technology: focus on Apache Spark
 - Empower users to analyze data beyond what is possible today
 - Opens use cases for ML on controls data



Apache Spark

- Powerful engine, in particular for data science and streaming
 - Aims to be a “unified engine for big data processing”
- At the center of many “Big Data”, Streaming and ML solutions



Engineering Efforts to Enable Effective ML

- From “Hidden Technical Debt in Machine Learning Systems”, D. Sculley et al. (Google), paper at NIPS 2015

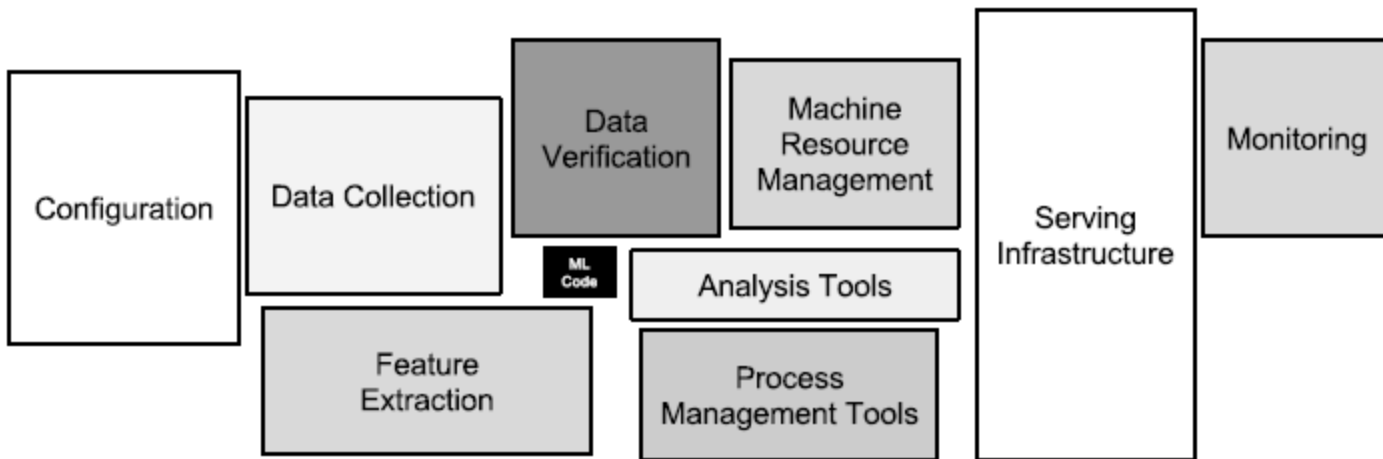


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Machine Learning with Spark

- Spark has tools for **machine learning at scale**

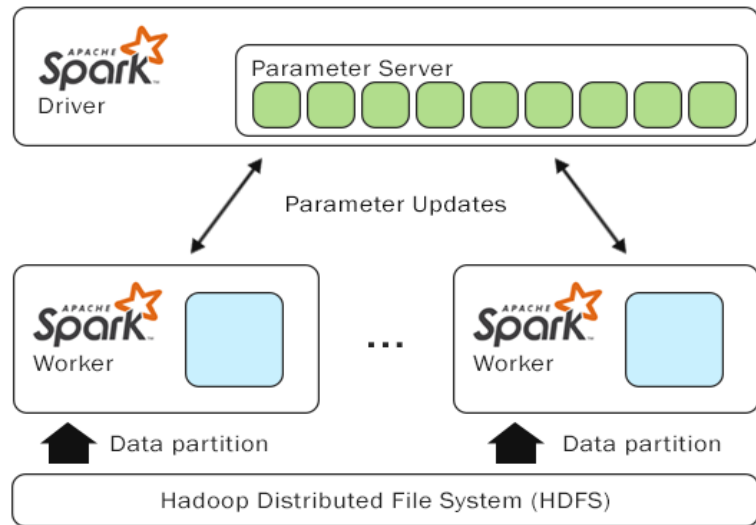
- Spark library MLlib

- Distributed deep learning

- Working on use cases with CMS and ATLAS
- We have developed an integration of Keras with Spark

- Possible tests and future investigations:

- Frameworks and tools for distributed deep learning with Spark available on open source:
 - BigDL, TensorFlowOnSpark, DL4j, ..
- Also of interest HW solutions: for example FPGAs, GPUs etc



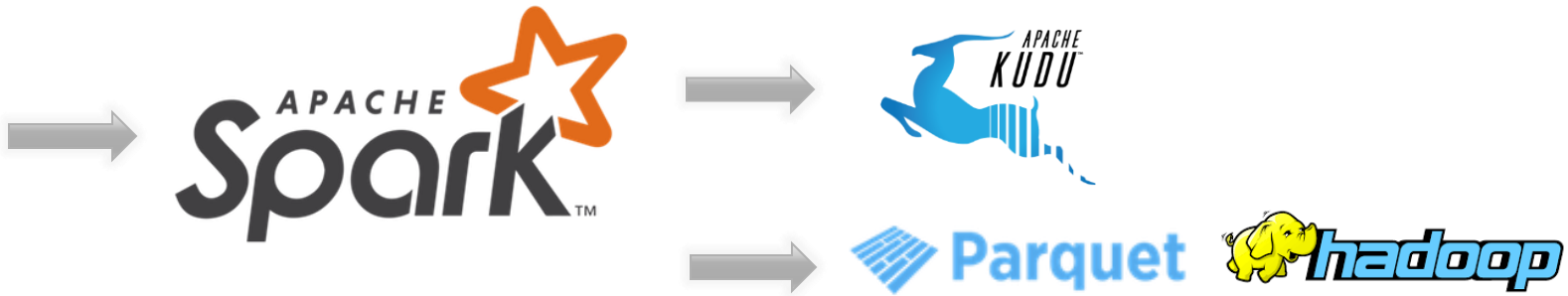
<https://github.com/cerndb/dist-keras>

Main developer: Joeri Hermans (IT-DB)

Spark as a Database Engine

- Spark SQL is now mature
 - Feature-rich, scalable, flexible
 - Combine it with data formats and storage solutions and will act as a relational database (for analytics)

Data
Analytics
(SQL)



Not Only Spark..

- Other components in the ecosystem for database-like workloads
- Analytics
 - Impala, a SQL engine written in C++
- Fast layer:
 - HBASE and Kudu
 - Streaming solutions

In the following,

Some additional thoughts on
challenges and opportunities

R&D: Hadoop and Spark on OpenStack

- Tests of deploying Hadoop/Spark on **OpenStack** are promising
- Appears a good solution to deploy clusters where local storage locality is not needed
 - Example: possible candidates for Spark clusters for physics data processing reading from EOS (or from remote HDFS)
- Also run tests of Hadoop clusters with local storage
 - Using ad-hoc and “experimental configuration” in particular for the storage mapping, thanks to the collaboration with OpenStack team at CERN
 - Promising results, we plan to further explore

R&D: Architecture and Components Evolution

- **Architecture** decisions on data locality
 - Currently we deploy Spark on YARN and HDFS
- **Investigating:** Spark clusters without directly attached storage?
 - Using EOS and/or HDFS accessed remotely?
 - EOS integration currently being developed for Spark
 - Spark clusters “on demand” rather than Yarn clusters?
 - Possibly on containers

Scale Up – from PB to EB in 5-10 years?

- Challenges associated with **scaling** up the workloads
 - Example from the CMS data reduction challenge: 1 PB and 1000 cores
 - Production for this use case is expected **10x** of that.
 - New territory to **explore**
- HW for tests
 - CERN clusters + external resources, example: testing on Intel Lab equipment (16 nodes) in February 2017

Challenges

- Platform
 - Provide evolution for **HW**
 - Build robust service for critical platform (NXCALS and more) using **open source** software solutions in constant **evolution**
- Service
 - Evolve service configuration and **procedures** to fulfil users needs
- Knowledge
 - Only 2-3 years **experience**
 - **Technology** keeps evolving

Training and Teaching Efforts

- Intro material, delivered by IT-DB
 - "Introduction and overview to Hadoop ecosystem and Spark“, April 2017. Slides and recordings at: <https://indico.cern.ch/event/590439/>
 - 2016 tutorials: <https://indico.cern.ch/event/546000/>
- More **training sessions**:
 - Planned for November 2017, presentations + hands-on
 - Introduction and overview to Hadoop ecosystem and Spark. Subscribe at: https://cta.cern.ch/cta2/f?p=110:9:207485681243790::::X_STATUS,X_COURSE_ID:D,5331
 - See also presentations at the Hadoop Users Forum: <https://indico.cern.ch/category/5894/>

Community

- Recent activity on configuration
 - Contacted with Hadoop admins at SARA
 - Also contacts with Princeton (via CMS Bigdata project)
- Opportunities to share with **industry** and “Big Data” communities at large
 - See presentations by CERN Hadoop service at Kafka Summit, Strata Data, Spark Summit, XLDB
- More **sites** interested in Hadoop and Big Data
- **Opportunities to share** experience across WLCG sites and with other **sciences**

Conclusions

- **Hadoop**, Spark, Kafka services at CERN IT
 - Analytics, streaming, ML, logging/controls
- Our goals: **service** delivery and working on selected **projects** with the user community
- We are growing
 - Service (new NXCal platform for accelerator logging)
 - Experience and **community**