SPARK+AI
SUMMIT EUROPE

Experience of Running Spark on Kubernetes on OpenStack for High Energy Physics Workloads

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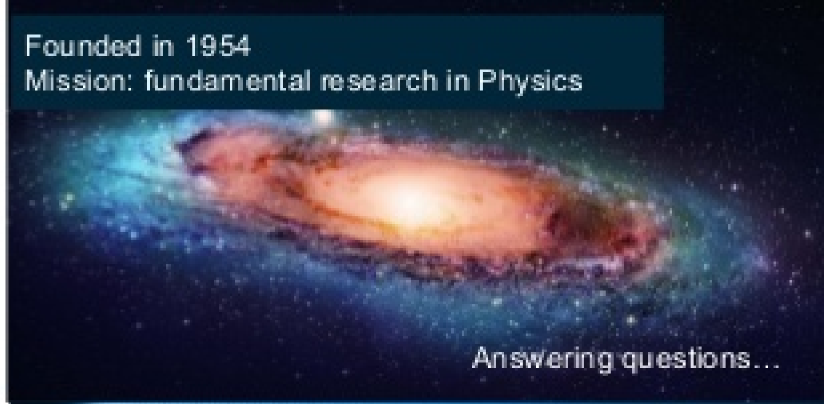
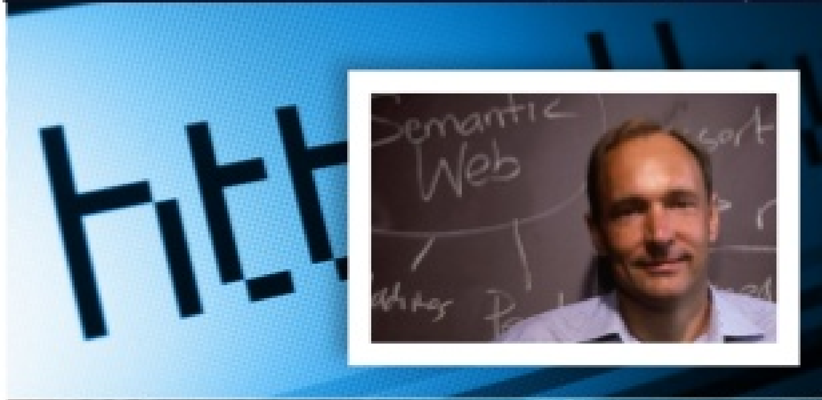
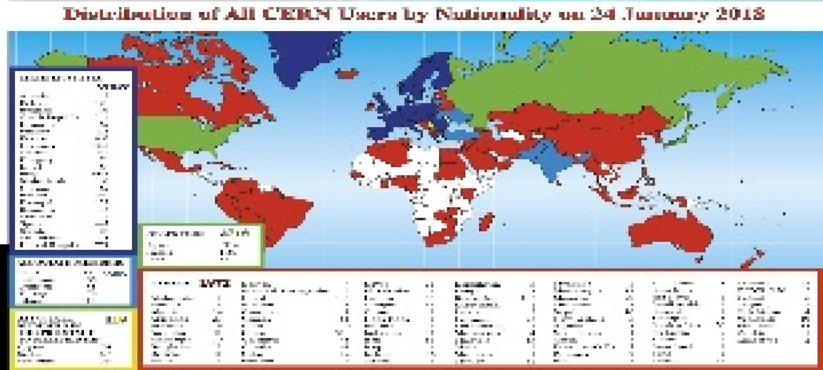
#SAISEco11

CERN

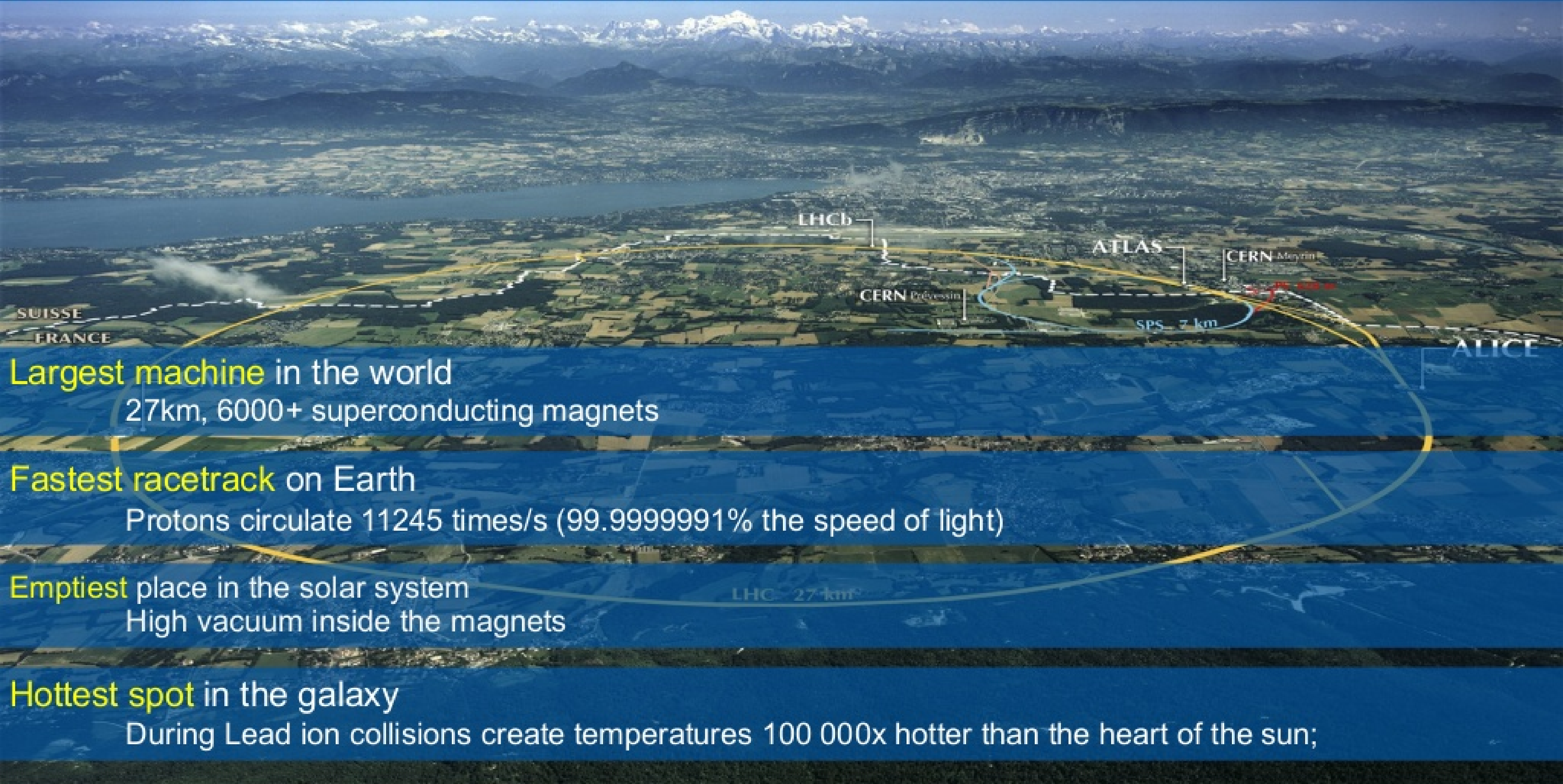
- CERN - European **Laboratory** for Particle Physics
- The place where the **Web** was born
- Home of the **Large Hadron Collider** and 4 big Experiments:
  - ATLAS ~ CMS ~ LHCb ~ ALICE
- 22 member states + 6 associate members + **world-wide** collaborations
  - ~3000 Members of Personnel
  - ~12,000 users
  - ~1000 MCHF yearly budget







The Large Hadron Collider (LHC)



Largest machine in the world
- 27km, 6000+ superconducting magnets

Fastest racetrack on Earth
- Protons circulate 11245 times/s (99.9999991% the speed of light)

Emptiest place in the solar system
- High vacuum inside the magnets

Hottest spot in the galaxy
- During Lead ion collisions create temperatures 100 000x hotter than the heart of the sun;

CERN Data Centre

- Physics data are aggregated in the CERN Data Centre, where initial data reconstruction of physics events is performed
- A remote extension of the CERN data centre is hosted in Budapest, Hungary. It provides the extra computing power required to cover CERN's needs.

~ 12.5 PB per month

~ 2 PB accessed every day

~ 4 megawatt of electricity

	Meyrin Data Centre	Wigner Extension	TOTAL
Servers	11 500	3 500	15 000
Processor cores	174 300	56 000	230 300
Disks	61 900	29 700	91 600 (280 PB capacity)
Tape Cartridges			32 200 (~ 400 PB capacity)

Data at Scale @ CERN

- **Physics data** – Today we use WLCG to handle it
  - Optimised for physics analysis and concurrent access
  - ROOT framework - custom software and data format
  - Early stage experimental work ongoing to use Spark for physics analysis

- **Infrastructure data**
  - Accelerators and detector controllers
  - Experiments Data catalogues (collisions, files etc.)
  - Monitoring of the WLCG and CERN data centres
  - Systems logs

Apache Spark @ CERN

- **Current state-of-the-art**
  - Spark running on top of YARN/HDFS. Typically processing happens on the same cluster of machines as storage (data locality)
  - In total **~1850 physical cores** and 15 PB capacity

Cluster Name	Configuration	Software Version
Accelerator logging	20 nodes (Cores 480, Mem - 8 TB, Storage – 5 PB, 96GB in SSD)	Spark 2.2.0 – 2.3.1
General Purpose	48 nodes (Cores – 892,Mem – 7.5TB,Storage – 6 PB)	Spark 2.2.0 – 2.3.1
Development cluster	14 nodes (Cores – 196,Mem – 768GB,Storage – 2.15 PB)	Spark 2.2.0 – 2.3.1
ATLAS Event Index	18 nodes (Cores – 288,Mem – 912GB,Storage – 1.29 PB)	Spark 2.2.0 – 2.3.1

Apache Spark @ CERN

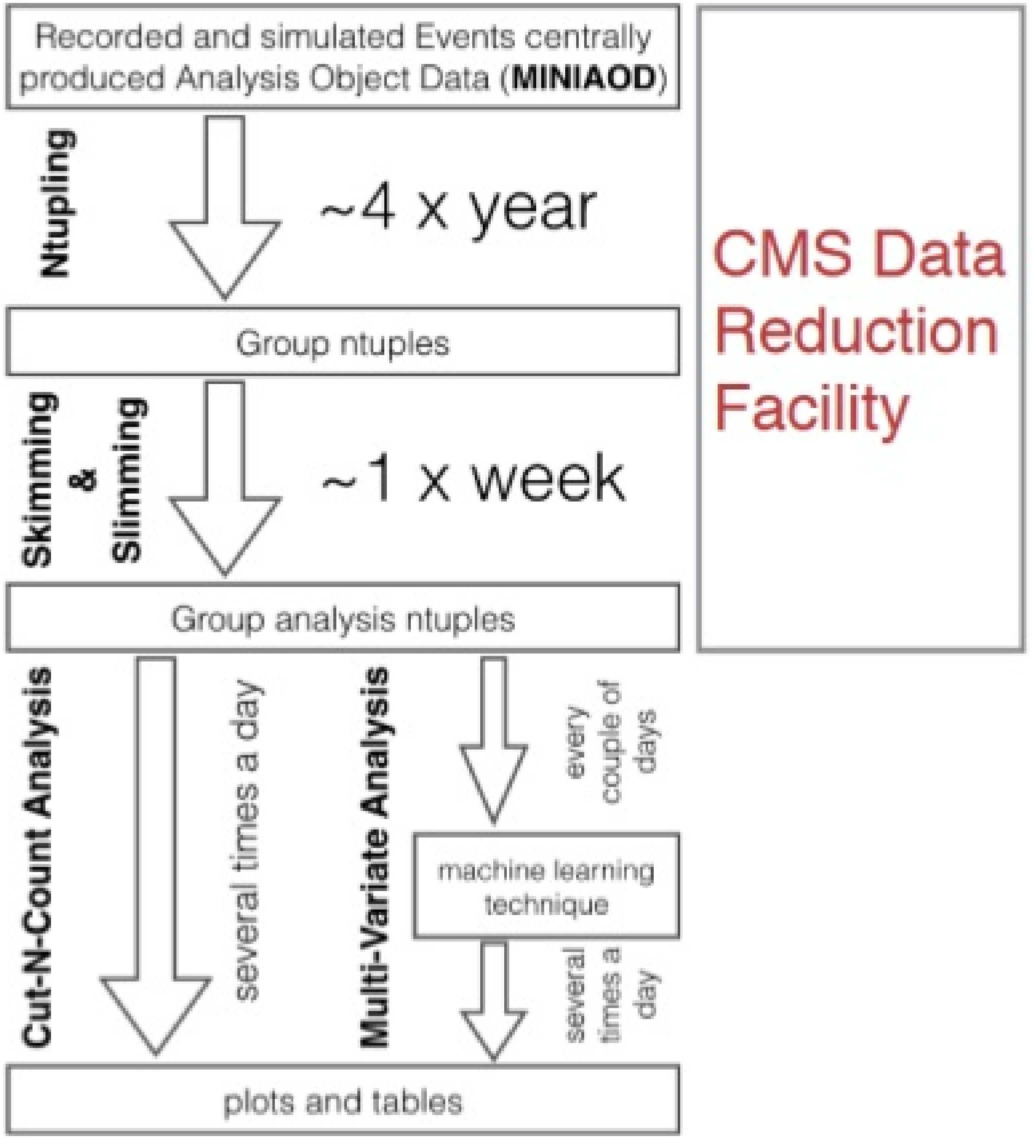
- **Current state-of-the-art**
  - Stable and predictable production workloads from our user communities
  - Physical machines allocated – means no resource elasticity, no isolation of workloads, compute coupled with data storage
  - Ad-hoc workloads from physics users interested analyzing data at scale using external storages (EOS). Physics analysis limited to the capacity and resources of shared Spark/Hadoop clusters.

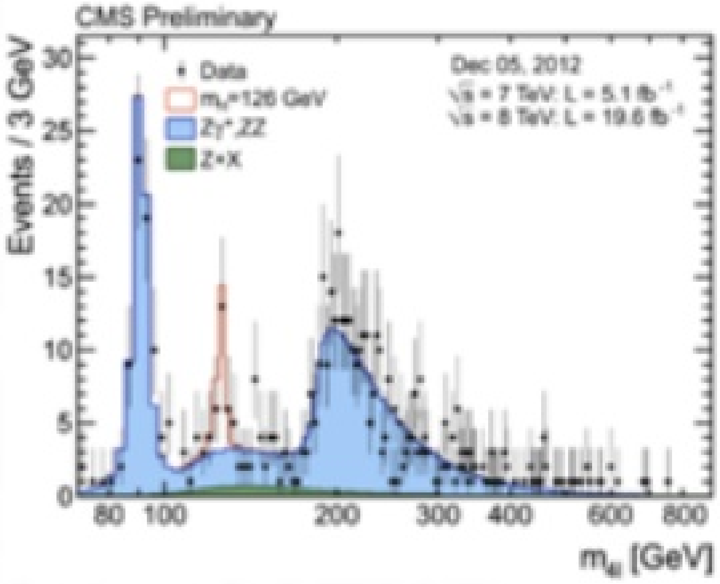
New Programming / Analysis Model for Physics data
- Data and Operational Challenges

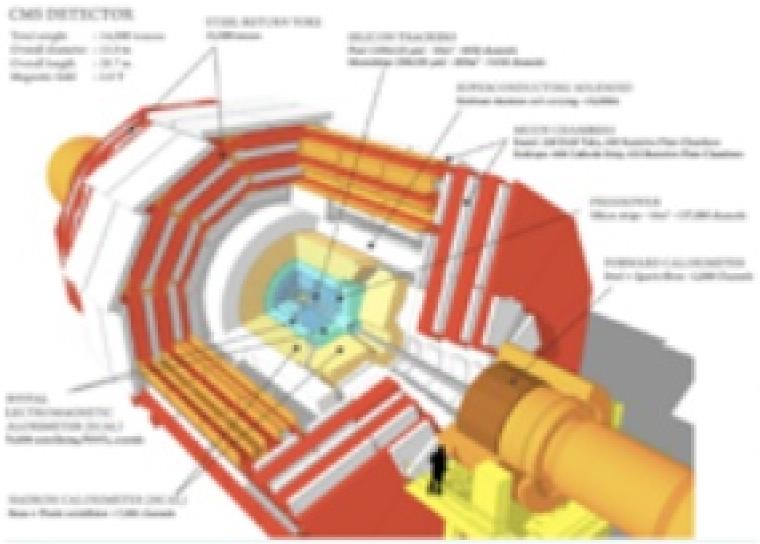
Data and Operational Challenges

- Data volumes expected to grow dramatically with HL-LHC
  - Annual growth at 20-30%
- Decrease time-to-physics
  - On-demand generation of physics n-tuples
- Resource Elasticity
- Isolation of workloads
- Physics data stored externally in EOS – CERN custom built data storage
- Usage of industry big-data solutions

CMS Data Reduction Facility







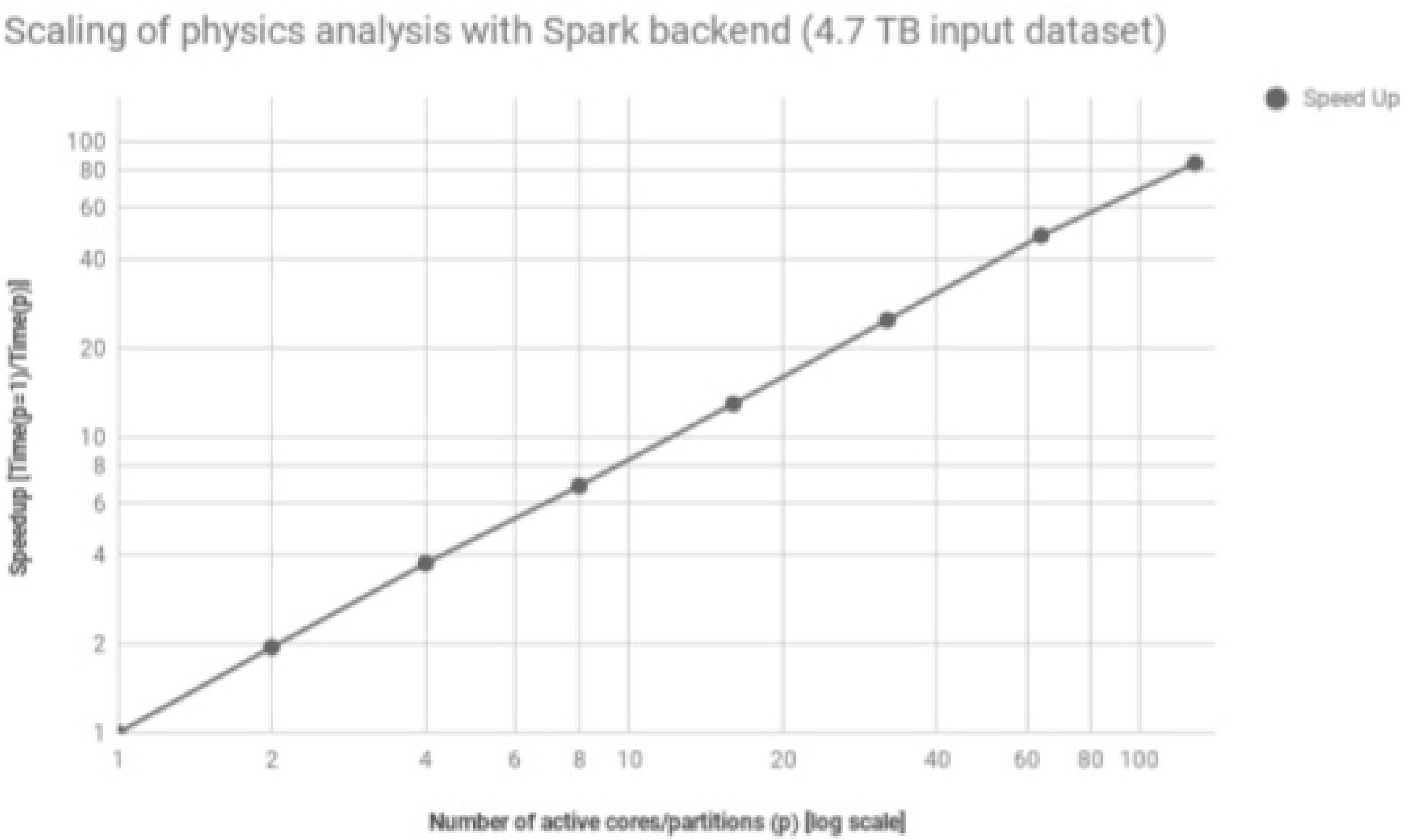
On-demand reduction of large datasets based on complicated user criteria

Input dataset ~ petabytes and requires 1000's cores

Reproducibility is key in the physics research world!

Interactive physics data analysis using notebooks

- To propose a time-efficient way to perform analysis of extensive amounts of data in CERN
- To investigate impact and usefulness of external solutions for HEP computing needs
- To prepare a ready model for future analyses performed in (TOTEM) experiments



Addressing the Challenges

Literature Study

„Cloud-native is an approach to building and running applications that exploits the advantages of the cloud computing model" [1]

Companies attempted cloud-native Spark deployments using Kubernetes Native resource scheduler implementation had experimental release in Apache Spark in March 2018.

Research from Google defends the hypothesis, that in cluster computing disk-locality is becoming irrelevant nowadays [2]

Databricks and Accenture Labs benchmarked Spark with data in external storages (S3/GCS) compared to HDFS. [3][4]

[1] „Kubernetes becomes the first project to graduate from the cloud native computing foundation."
[2] „Disk-Locality in Datacenter Computing Considered Irrelevant"
[3] Databricks - „Top 5 Reasons for Choosing S3 over HDFS"
[4] Accenture Technology Labs - „Cloud-based Hadoop Deployments: Benefits and Considerations"

Separating Compute and Storage for Elastic Big Data

Data Locality

Spark

HDFS

Spark/YARN

Data External (network)

External Storage (EOS, S3, GCS + Kafka, HDFS)

Spark

Spark/YARN

Spark on Kubernetes

Separating Compute and Storage for Elastic Big Data

Data Locality

Spark

HDFS

- assumes **disk bandwidth is higher** than **storage throughput over network**

Data External (network)

External Storage (EOS, S3, GCS + Kafka, HDFS)

Spark

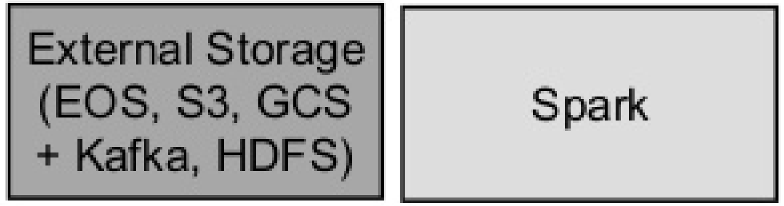
- assumes mass **storage throughput higher than** cluster **disk bandwidth**

Separating Compute and Storage for Elastic Big Data

Data Locality

- assumes **disk bandwidth is higher** than **storage throughput over network**
- **limited elasticity** (both for computation and storage)

Data External (network)



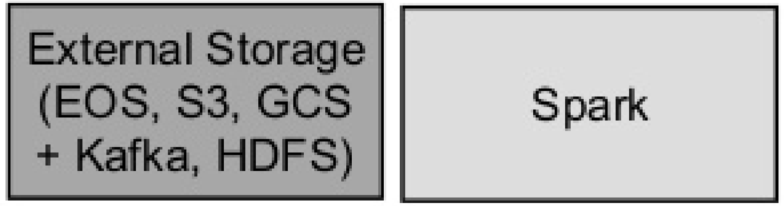
- assumes mass **storage throughput higher than** cluster **disk bandwidth**
- allows **compute not** being **bound** to **storage** (with cloud elasticity)

Separating Compute and Storage for Elastic Big Data

Data Locality

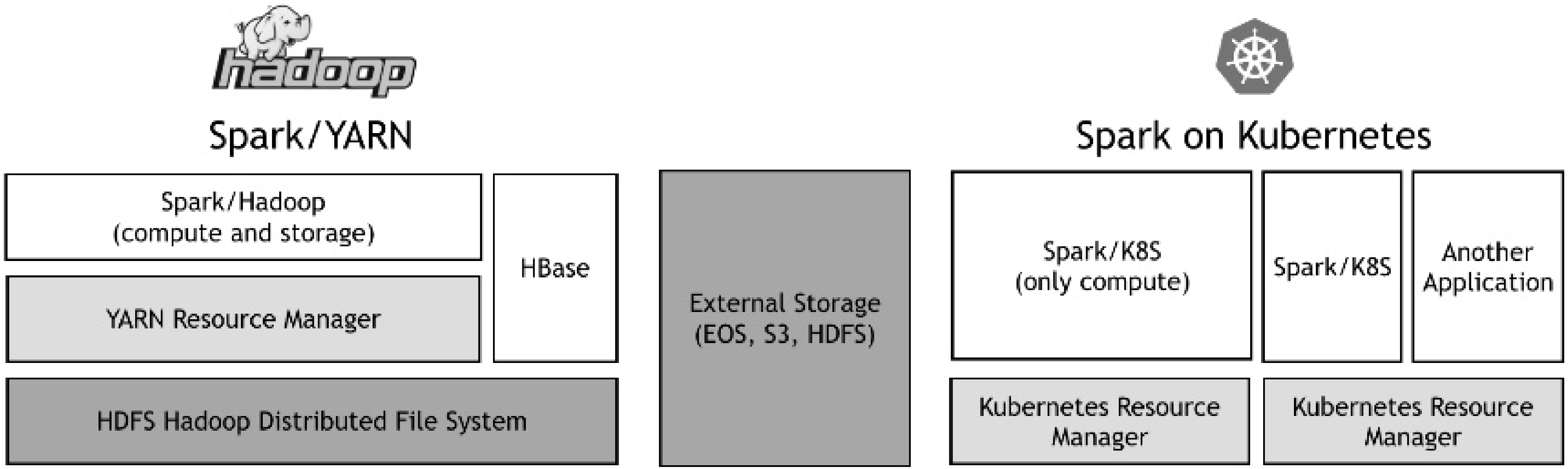
- assumes **disk bandwidth is higher** than **storage throughput over network**
- **limited elasticity** (both for computation and storage)
- **avoids high network bandwidth** for analysis on large datasets

Data External (network)



- assumes mass **storage throughput higher than** cluster **disk bandwidth**
- allows **compute not** being **bound** to **storage** (with cloud elasticity)
- assumes **network** delivers data **to CPU** faster than **local disks**, might generate **high traffic**

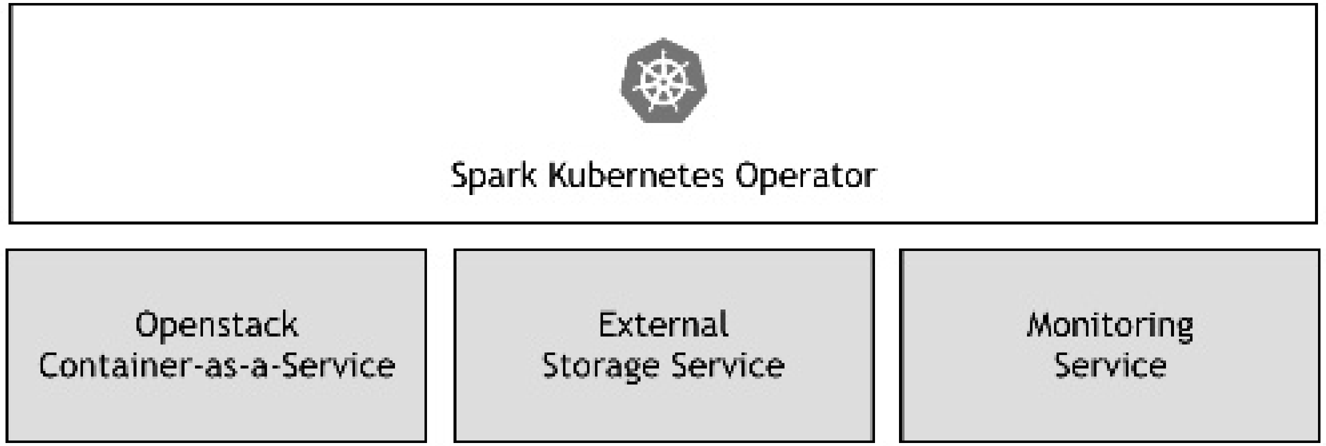
Possible solution for storage elasticity



- **mass storage** services are **easier/cheaper to scale**
- **data stored on disk** can be **large**, and **compute** nodes can be **adjusted to compute needs**

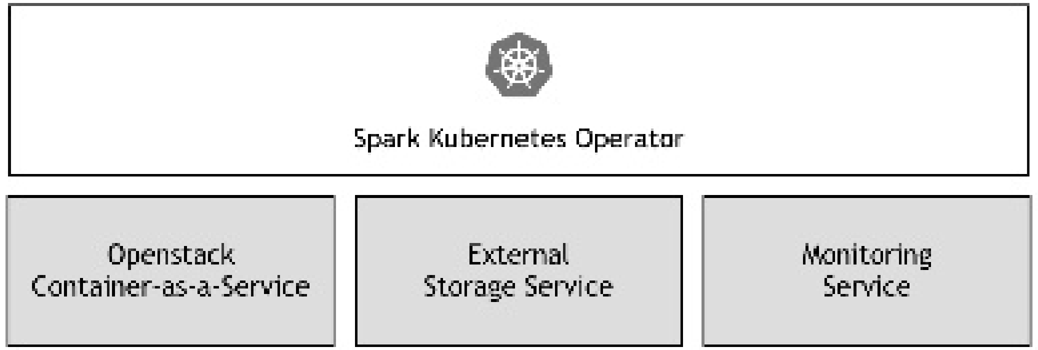
Possible solution for storage and compute elasticity and reproducibility

- Openstack CCE (**Cloud Container Engine)** with **Kubernetes** provides **compute elasticity** and **authentication** mechanism (certificates).



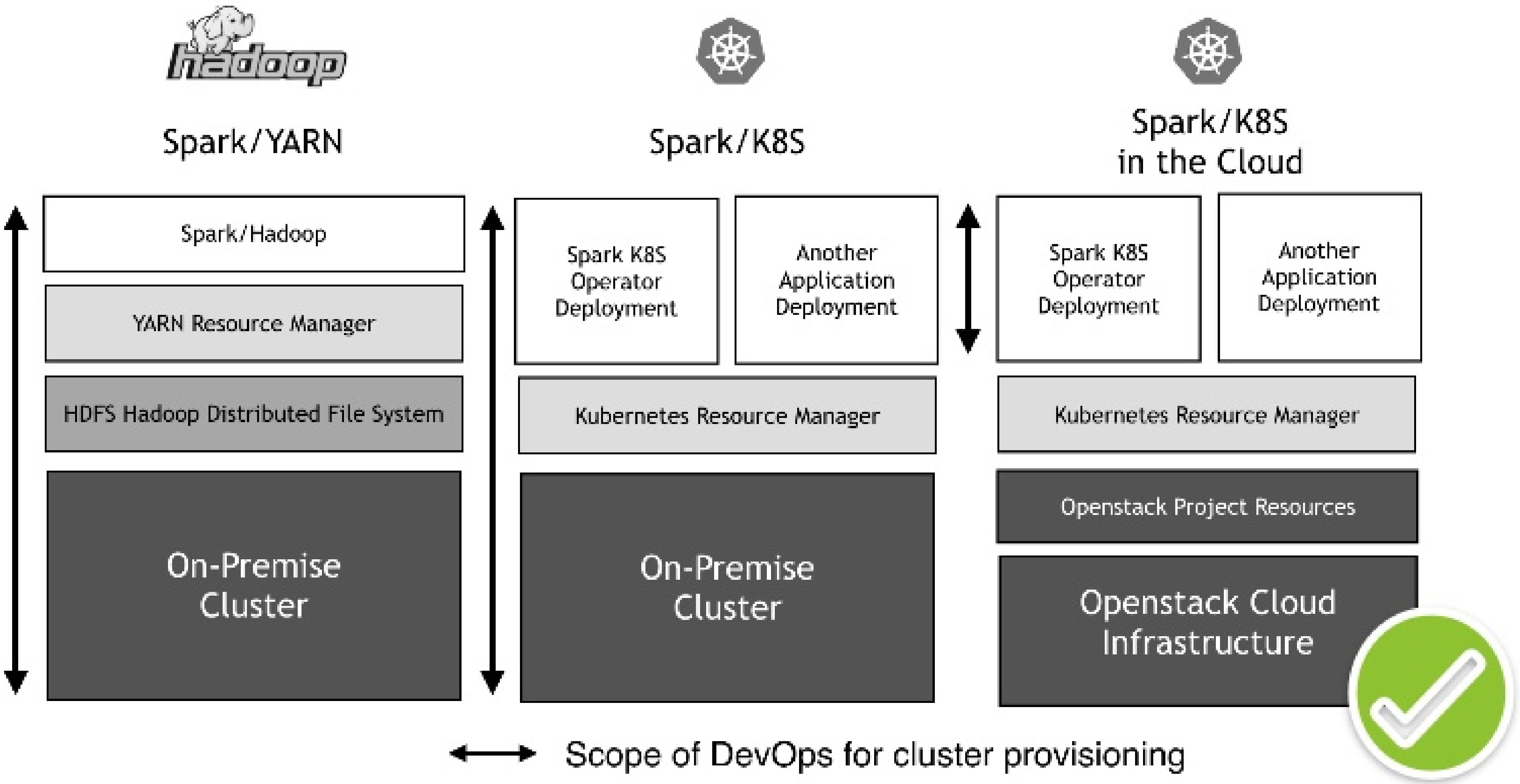
Possible solution for storage and compute elasticity and reproducibility

- Openstack CCE (**Cloud Container Engine)** with **Kubernetes** provides **compute elasticity** and **authentication** mechanism (certificates).
- **Separation** of monolithic **services simplifies operational effort**
- Just **Spark-Submit with Kubernetes** only allows to create drivers and executors (not so friendly to manage).
- **Spark K8S Operator** bring feature parity known from YARN (managing Spark Applications)
- Spark Operator gives **idiomatic submission**, **application restart policies**, **cron support**, **custom volume/config/secret mounts**, **pod affinity/anti-affinity**



[1] https://github.com/GoogleCloudPlatform/spark-on-k8s-operator

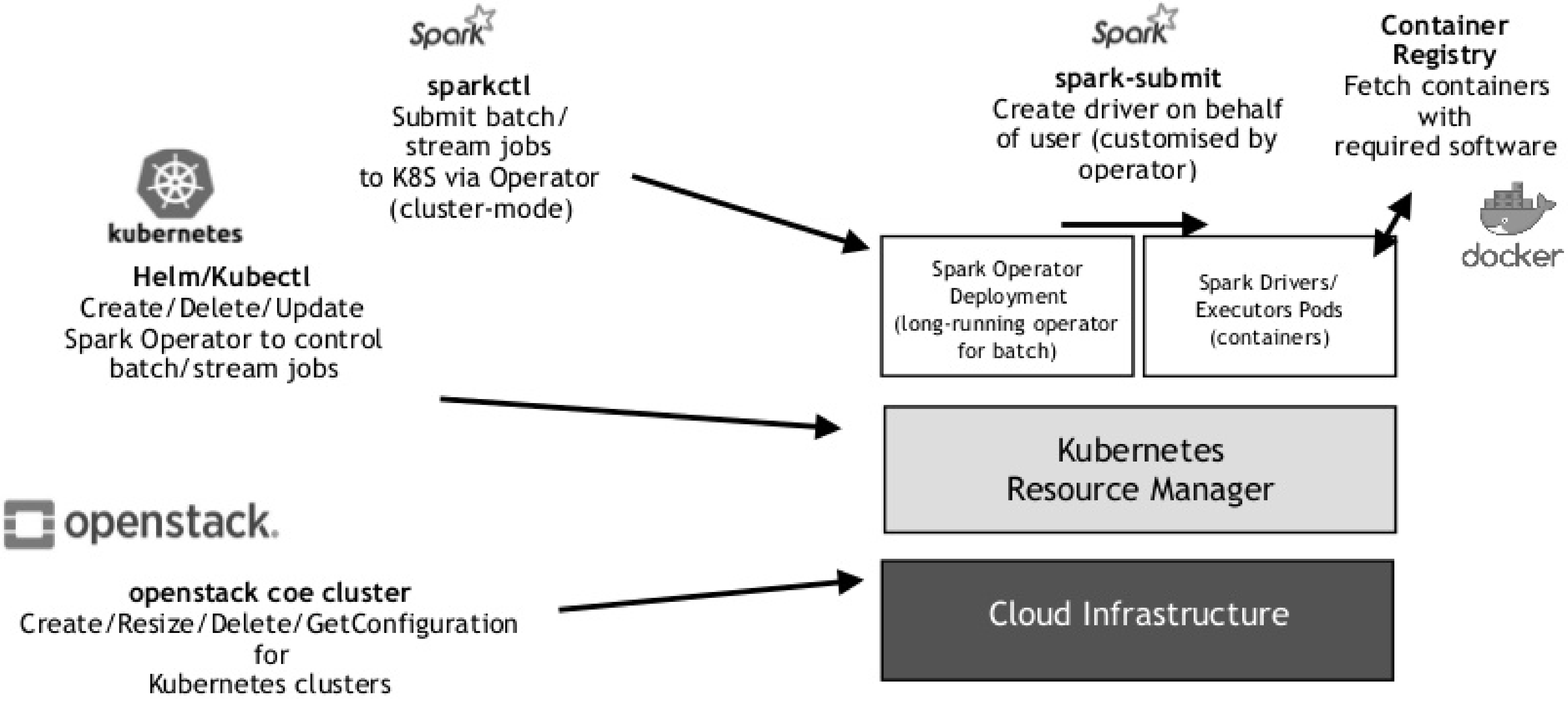
Container as a service to automate deployment



Evaluating Spark on Kubernetes properties and demo

Compute Elasticity

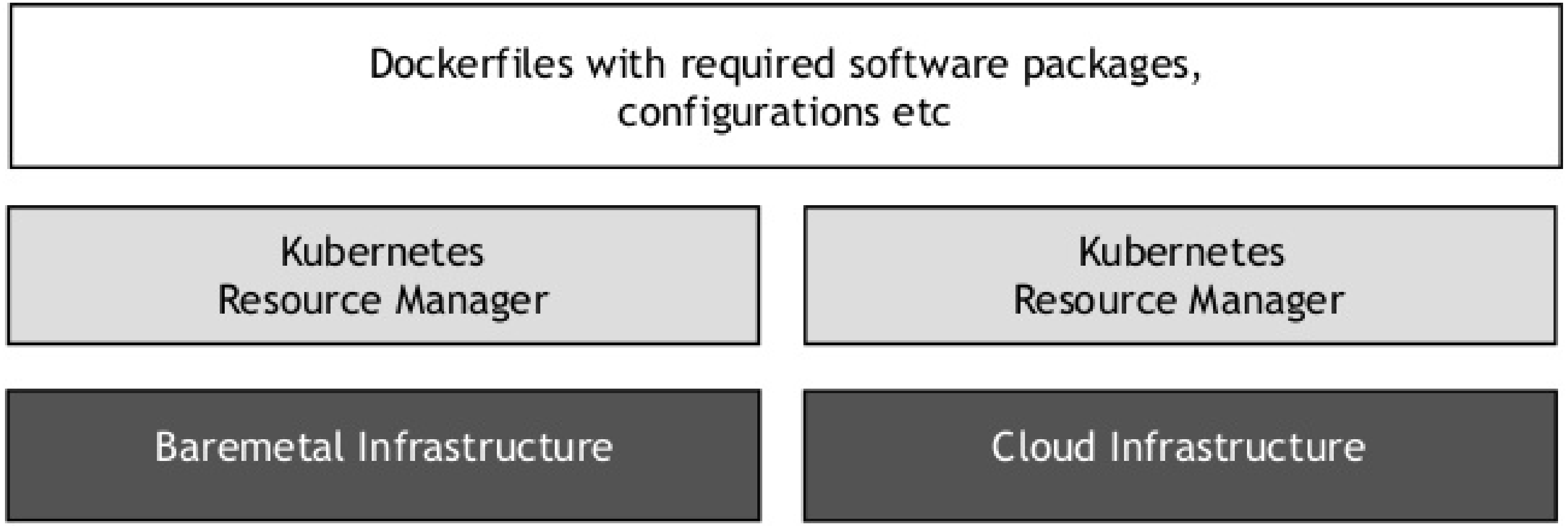
Cloud Container Engine



Workflow Reproducibility

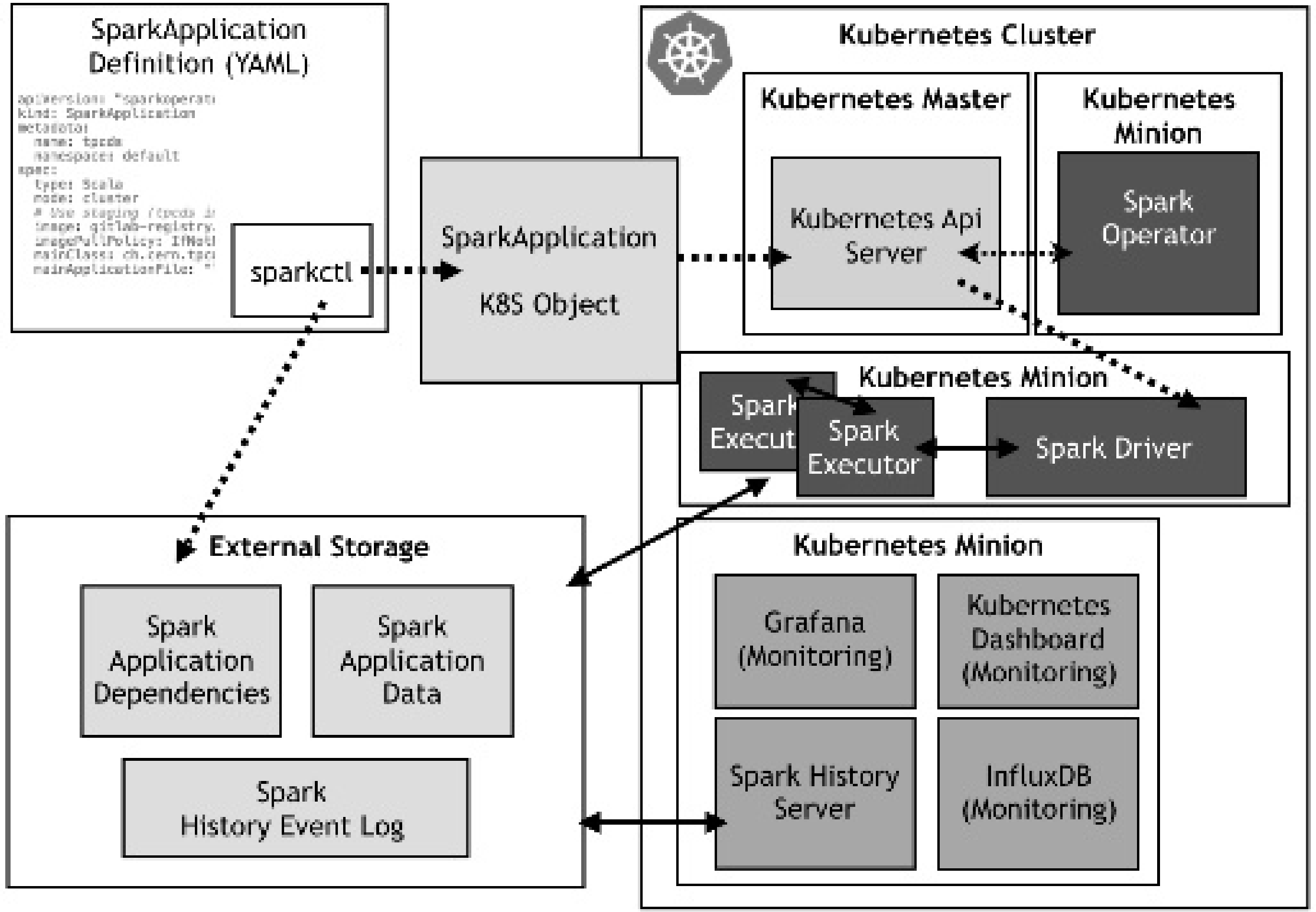
Docker containers

- Kubernetes and use of containers allows Spark developers to build their **isolated** and **reproducible environments**
- Encapsulate software packages, libraries, configurations



Management of Spark Applications

Kubernetes Operator for Apache Spark

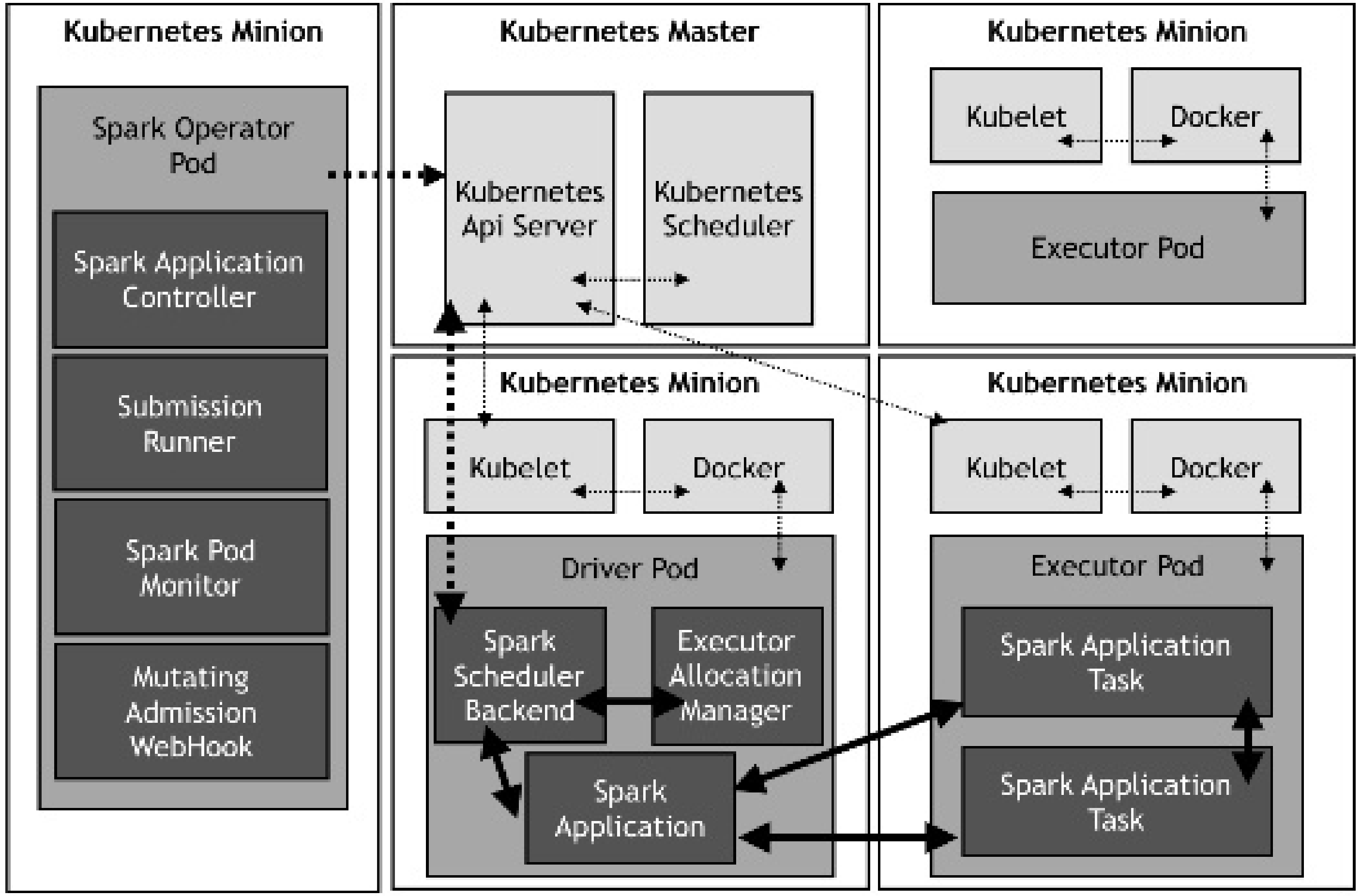


- Operator watches for create/delete/ update events of SparkApplication
- Spark Operator executes spark-submit with required configurations
- Data is uploaded/read from external storage service, and monitoring is realised with internal/ external monitoring tools

https://github.com/GoogleCloudPlatform/spark-on-k8s-operator

Management of Spark Applications

Kubernetes Operator for Apache Spark



- **Spark Application Controller** handles restarts and resubmissions.
- **Submission Runner** executes spark-submit
- **Spark Pod Monitor** reports updates of pods to controller
- **Mutating Admission WebHook** handles customisation of Docker containers and their affinities

https://github.com/GoogleCloudPlatform/spark-on-k8s-operator

Persistent Storage for cloud-native

Data over network - available solutions with CERN Openstack Cloud

Persistent Storage Feature	Network Volume Mounts	Filesystem Connectors	Object Storage Connectors	Monitoring Storage
Example	**CephFS [1]**, **CVMFS [2]**, other [3]	**EOS/XRootD [4]**, HDFS external, no data locality	**Ceph S3**, GCS [5]	**InfluxDB/Grafana**, Stackdriver, Prometheus
Use-case	**Software Packages**, **Checkpoints, Events (History Server)**	**Data processing**, Events, Checkpoints	**Data processing, Events (History Server), Checkpoints**	**Statistics**
Spark Transactional Writes	-	Yes	Requires committer (Directory Committer Hadoop 3.1) [6]	-

[1] https://clouddocs.web.cern.ch/clouddocs/containers/tutorials/cephfs.html

[2] https://clouddocs.web.cern.ch/clouddocs/containers/tutorials/cvmfs.html

[3] https://kubernetes.io/docs/concepts/storage/storage-classes

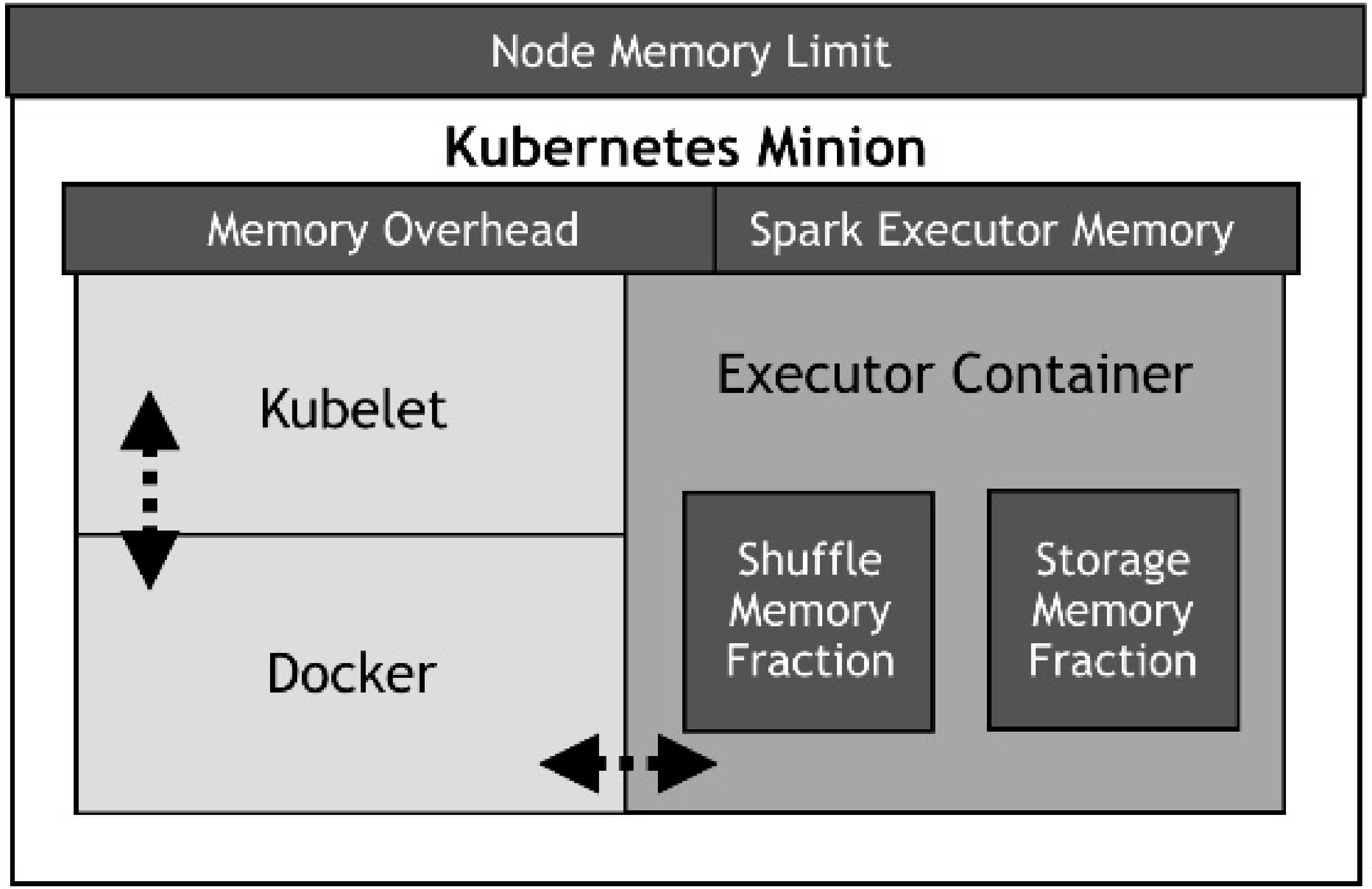
[4] https://github.com/cern-eos/eos, https://github.com/cerndb/hadoop-xrootd

[5] https://cloud.google.com/dataproc/docs/concepts/connectors/cloud-storage

[6] http://hadoop.apache.org/docs/r3.1.1/hadoop-aws/tools/hadoop-aws/committers.html

Memory management in Kubernetes

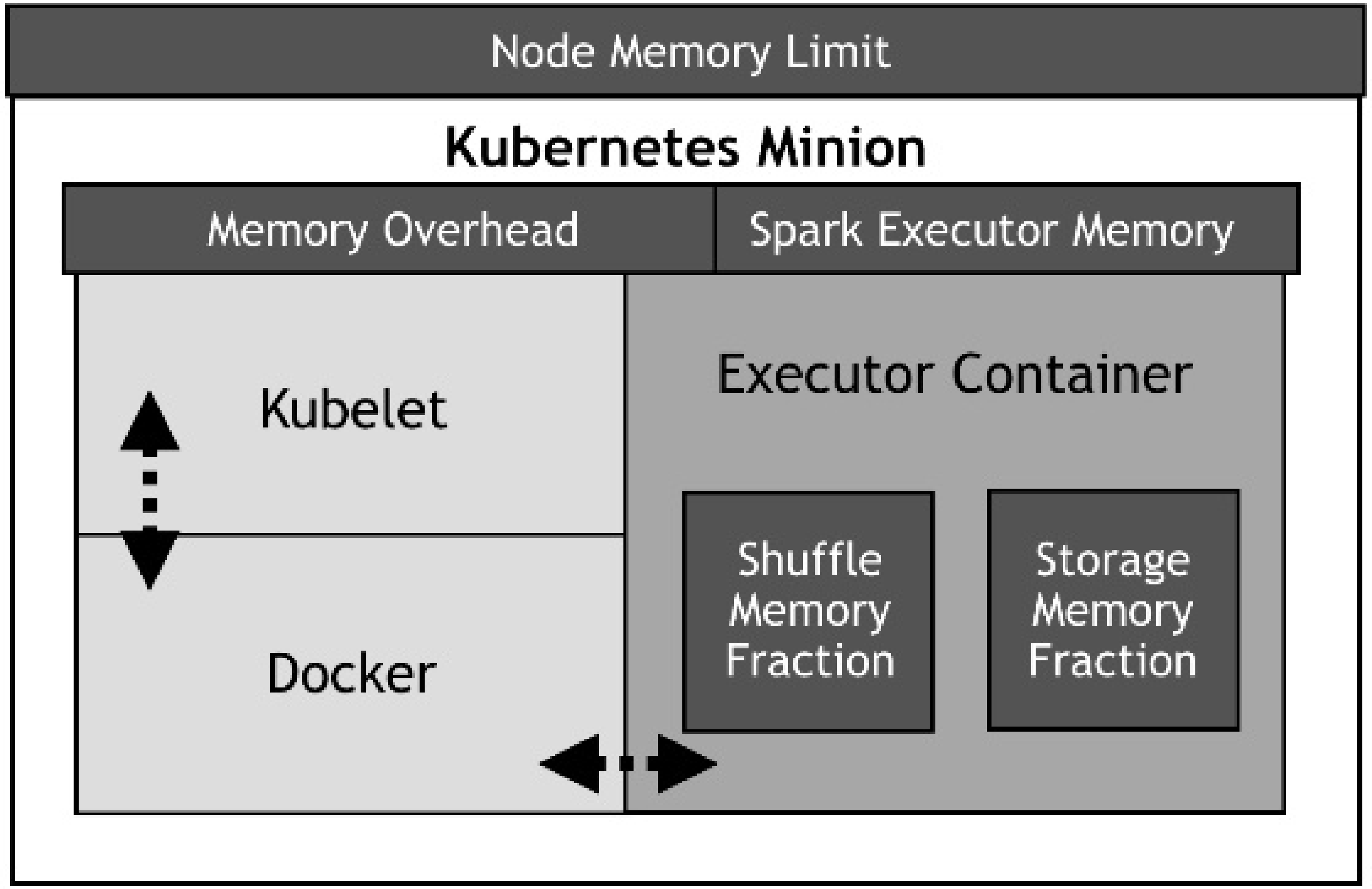
Spark and Kubernetes Nodes



- **Kubelet** monitors **memory** and **disk** available to the Node.
- Detecting **MemoryPressure** or **System Out Of Memory** and **reclaiming resources** from running containers **(OOMKilled errors)**

Memory management in Kubernetes

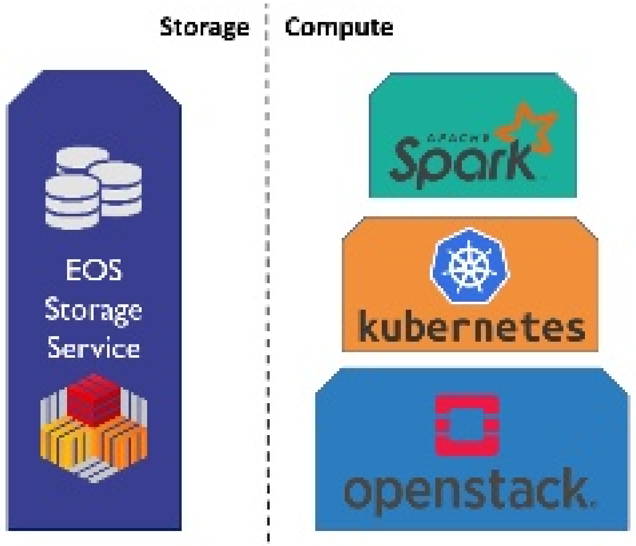
Spark and Kubernetes Nodes

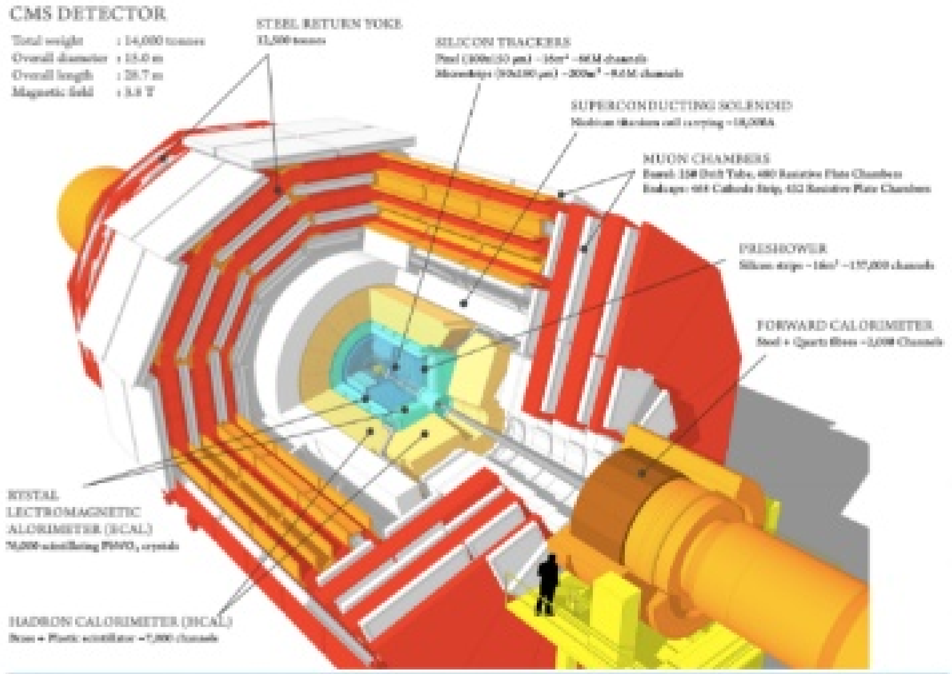


- **Kubelet** monitors **memory** and **disk** available to the Node.
- Detecting **MemoryPressure** or **System Out Of Memory** and **reclaiming resources** from running containers **(OOMKilled errors)**
- **MemoryOverheadFactor** - memory for **off-heap memory, non-JVM processes** (e.g. in case of Python higher limit) and processes required for **operation of container**.

Scaling Spark on Kubernetes

Data Reduction and Dimuon Mass Calculation on 20TB (target is 1 PB dataset)





- **1 VM** is **2CPU** and **12GB RAM**
- **Scaling Test** with 60 to 180 VMs
- **Load Test** with 500 VMs (200 hypervisors)

Scaling Spark on Kubernetes
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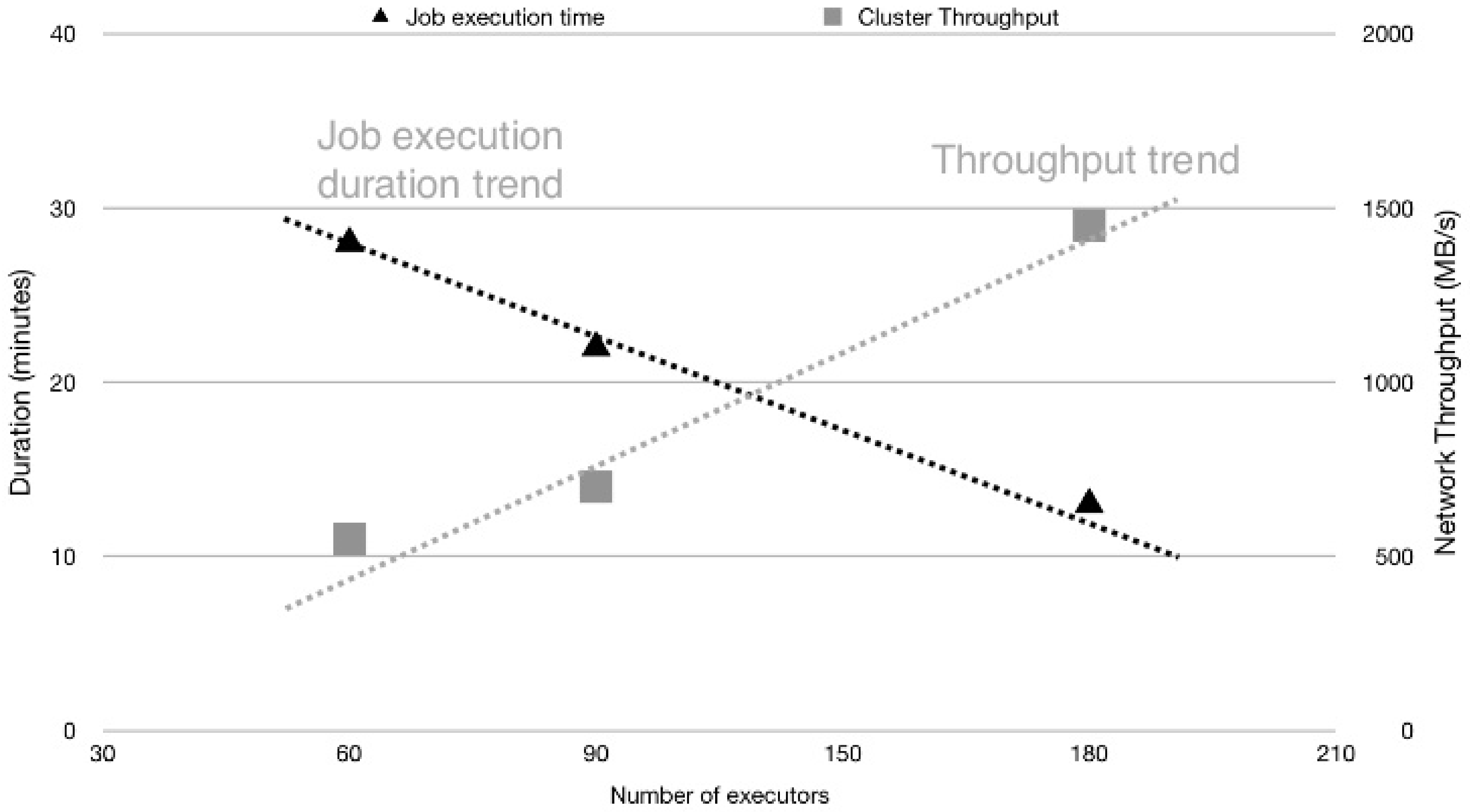


Spark Operator Demo

Create cluster

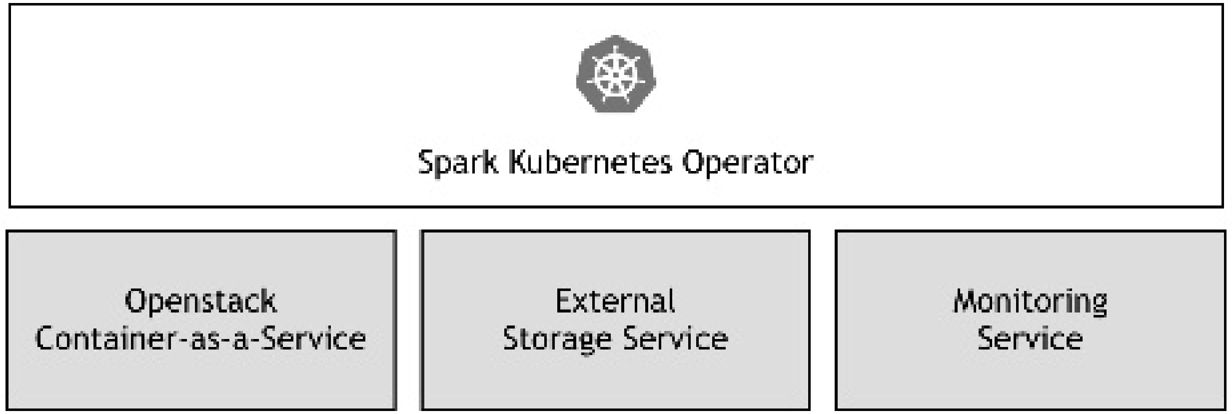
https://youtu.be/vuSLS7-JqQI

Conclusions and observations

- **Openstack provisions Kubernetes cluster** of 10s of nodes in automated fashion (**Cloud Container Engine,** Cloud Horizontal Autoscalers optional).

- **Kubernetes** allows **isolated** and **reproducible Spark, limited operational effort** with Docker containers.

- **Spark K8S Operator** provides management of Spark Applications similar to YARN ecosystem



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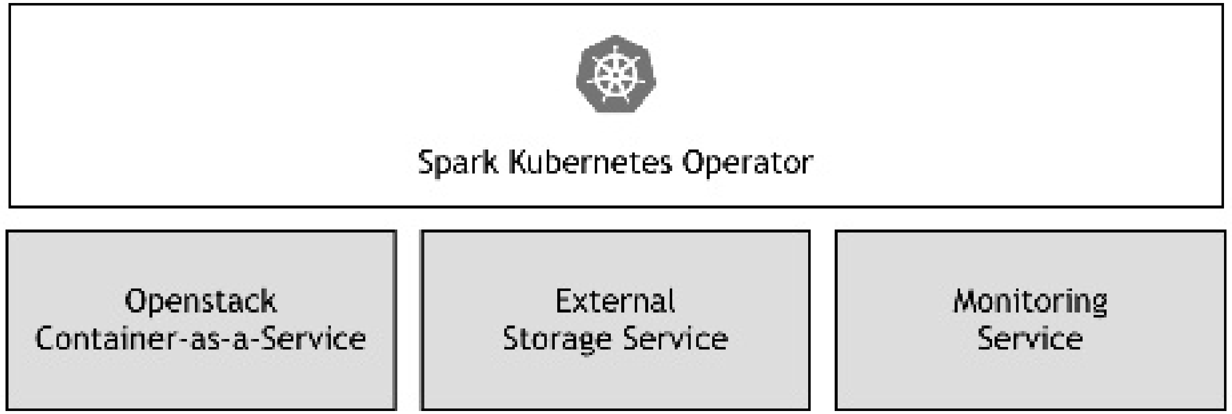
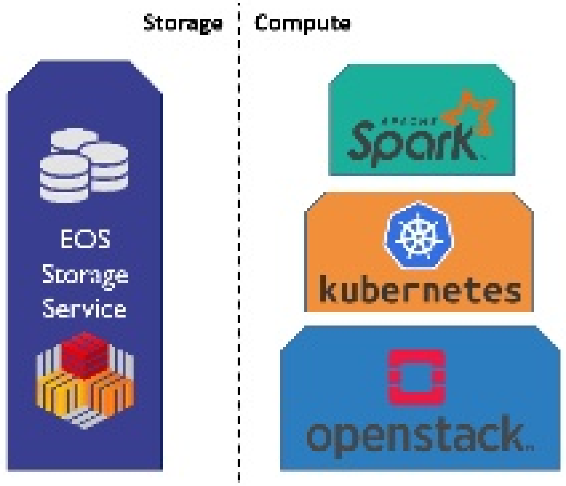


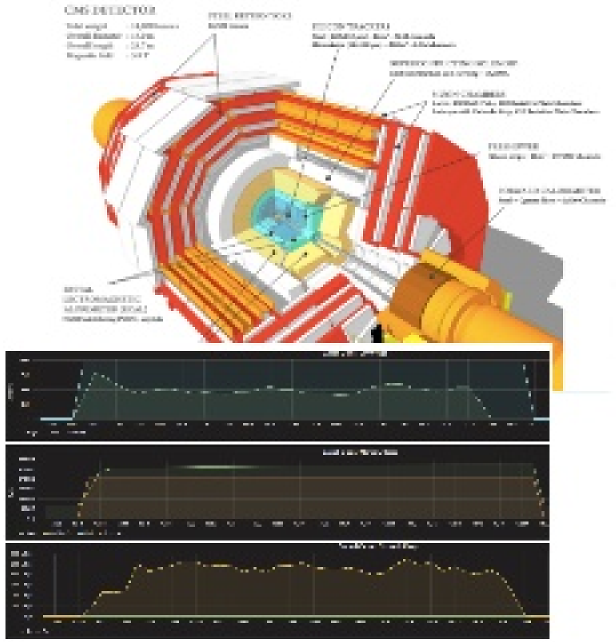
- **Data** is **external,** this has advantages but also drawbacks - **do you need data locality and why?**

- **Compute** cluster is **managed service**, storage can **scale separately** from **compute** or in the cloud.

- **Storage interoperability** (CephFS, EOS, S3 and GCS can serve more use-cases than just Hadoop)

Conclusions and observations





- **Without data locality**, **network** can be a **serious problem/bottleneck** (specifically in case of over-tuning or bugs). Monitoring at hand.
- Large shuffle writes problematic, **assumed compute VMs** and **large storage** space **is not available**. On other hand **SSD can be used cheaply**.
- **Multi-tenancy** still a question.

Conclusions and observations

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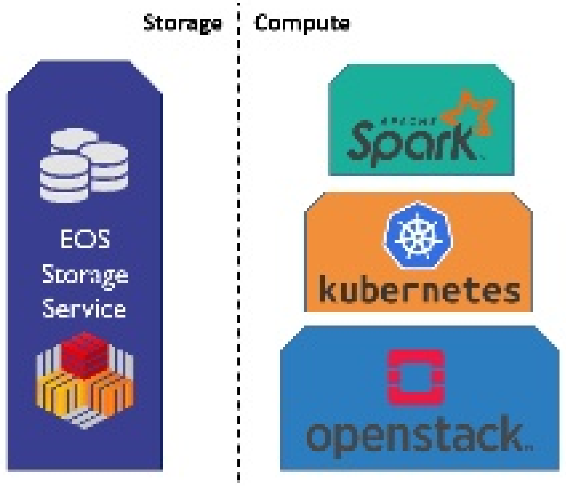

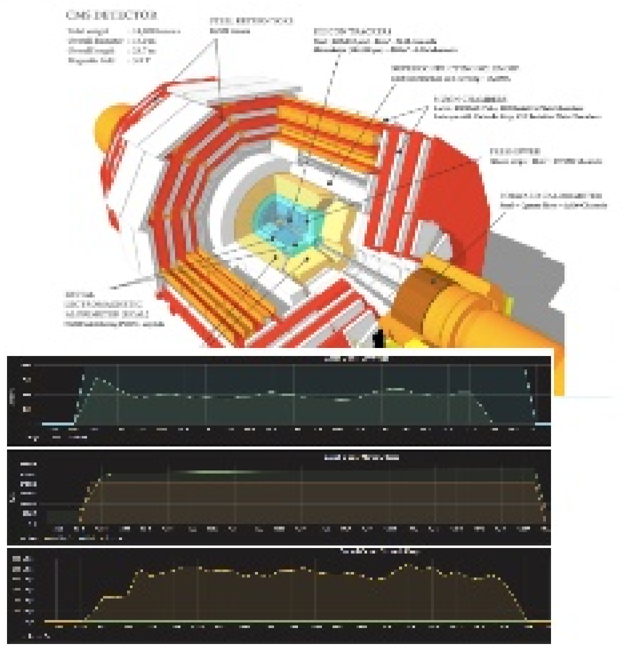

- No particular overhead between **K8S VMs** and **bare-metal YARN** with TPCDS Benchmark on similar hardware. Production YARN had more spikes than Cloud K8S due to shared environment.

- **Spark/YARN** had ~**40 nodes fixed**, **Spark/K8S** 500 VMs (**~200 nodes**) provisioned for **short time** period

Thank you

Questions?