The archive solution for distributed CMS WMAgents

Valentin Kuznetsov, Cornell University

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CMS Computing

Collaboration: 3800 people, 199 institutions, 43 countries

During 2017:

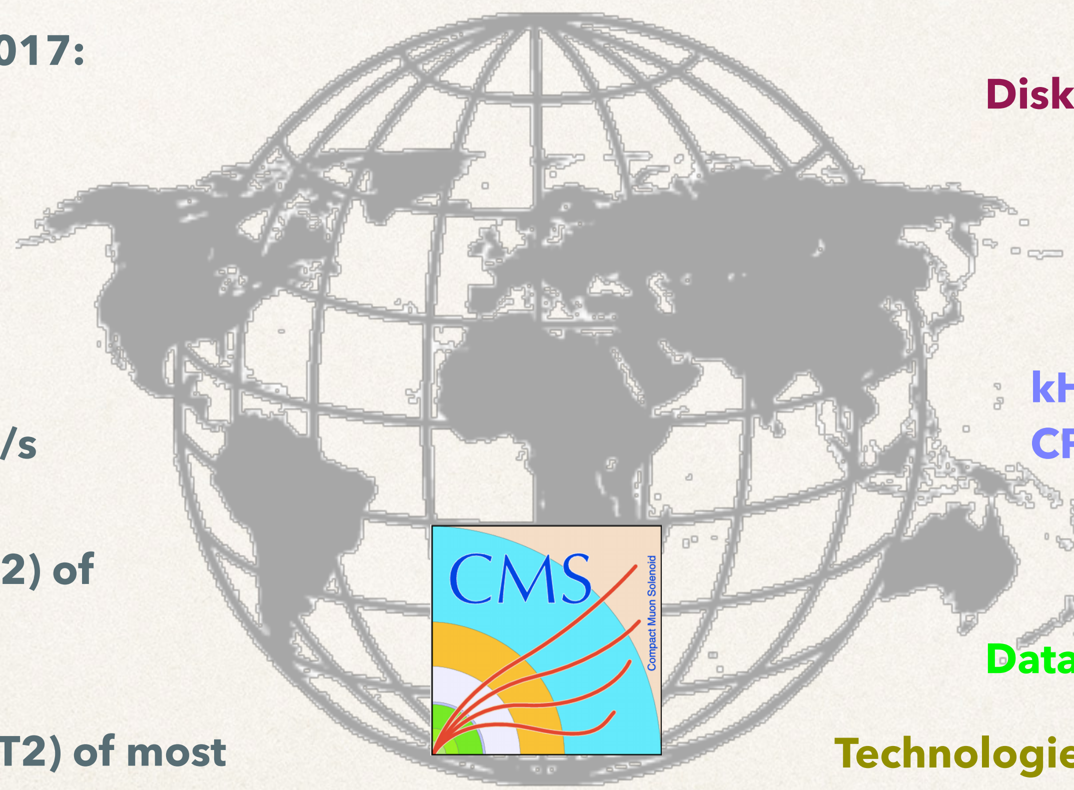
processed 30 B raw events

produced 16 B MC events

transferred 4 PB/week with average transfer rates 2-6 GB/s

deleted 85 PB (T1)/169 PB (T2) of **least** popular datasets

replicated 20 PB (T1)/80 PB (T2) of most **popular** datasets



	T0	T1	T2
Disk usage:	21 PB	39 PB	54 PB

	T0	T1
Tape usage:	49 PB	111 PB

kHS06-day	T0	T1	T2
CPU usage:	326	425	1133

Databases: ORACLE, CouchDB, MongoDB, …

Technologies: GRID, Cloud, XrootD, HDFS, Spark, ….

Code: C++, Python, C, Perl, Fortrans, Shell, Java, Go, …

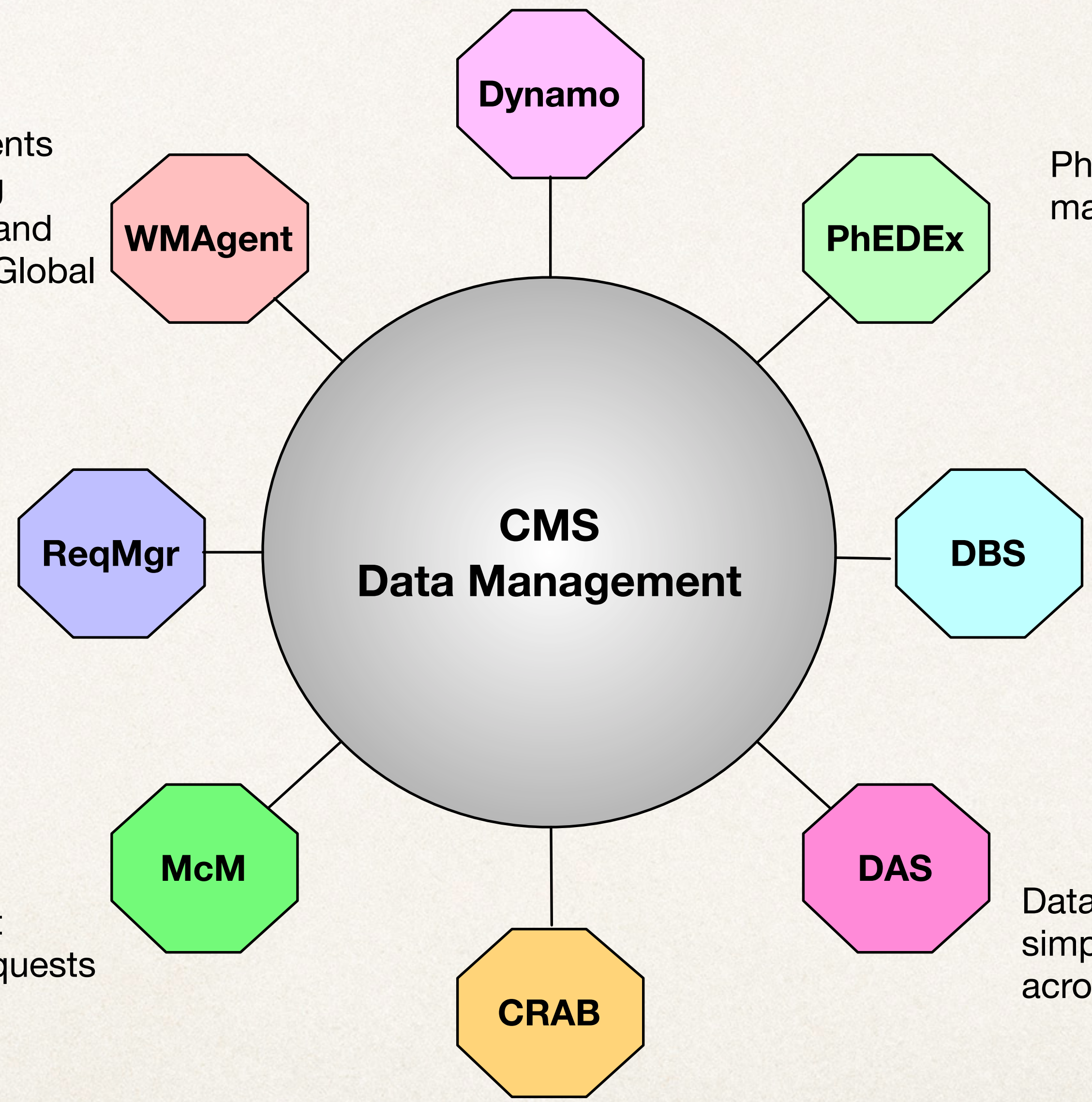
CMSSW: 190K commits, 1800 releases, 16M lines of code

CMS Data Management

Dynamo is dynamic data-placement system
moving PB of data among CMS sites.

Workflow Manager Agents responsible for splitting work jobs into chunks and sending them to CMS Global pool (HTCondor).

PhEDEx is a CMS data-transfer management system.



Request Manager is a main catalog for CMS production requests.

Data Bookkeeping System is CMS main data-catalog for storing dataset, block, files, runs, lumis meta-data

Monte Carlo Management system handles all MC requests

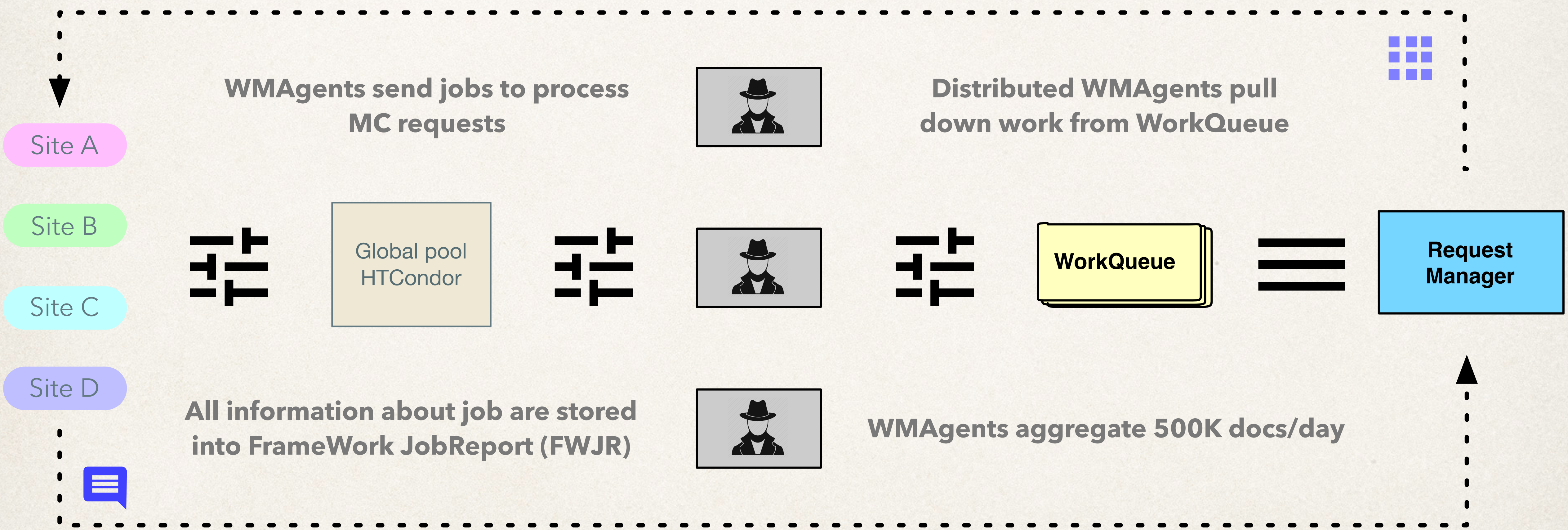
Data Aggregation System simplify user search queries across CMS data-services

CRAB is a utility to submit analysis jobs
to distributed computing resources

CMS Workflow Management System

Central Production System

Jobs are distributed across GRID sites



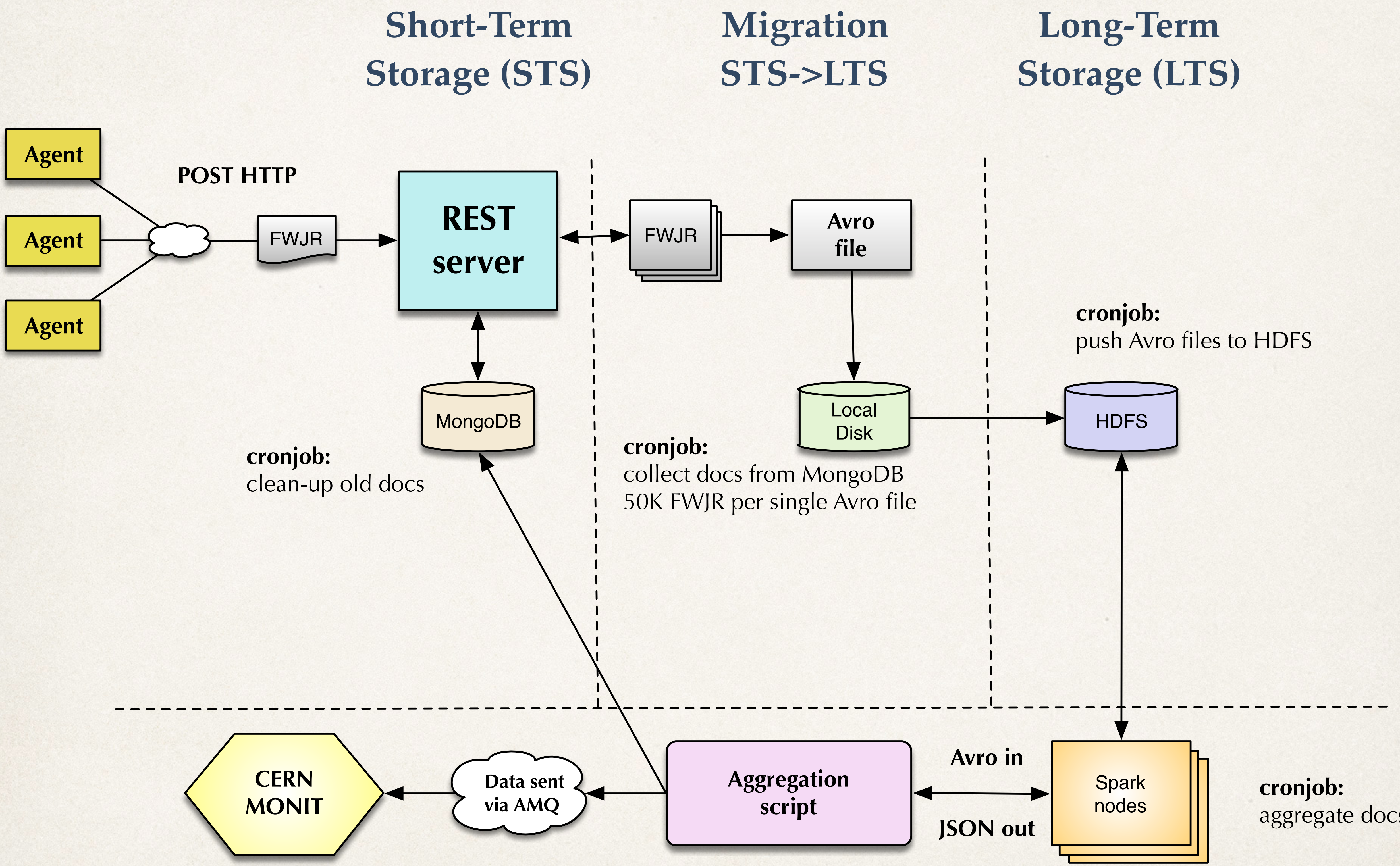
Job info are stored FrameWork JobReports

Requirements

- ~300K docs/day (10KB each), 3GB/day, 2TB/year
- Flexible schema and ability to extend it over time
  - unstructured JSON nested documents
- Flexible queries to look-up desired information
- Data aggregated across multiple metrics
- Web monitoring interface for job processing trends
- Have minimal impact on existing CMS infrastructure

Choices

- We decided to use **non-relational** data stores
  - Short-Term Storage is used to accumulate incoming data as fast as possible by storing them into document oriented MongoDB
  - Long-Term Storage is used to store data on HDFS file system
- We used **JSON** data-format for STS and **Avro** data-format for LTS
  - data consumed in JSON data-format, i.e. no changes to CMS codebase
  - data injected into HDFS in Avro (row-wise) data-format: schema evolution, language agnostic, compressible, append-able,
- We defined WMArchive **schema** upfront and convert data from STS to avto-data format before storing it on HDFS
- Separate data accumulation from data migration and clean-up procedure
- Interact with CMS DMWM stack via **RESTful** APIs



Separate aggregation Pipeline

Data look-up

- For STS we rely on Mongo QL which supports reach syntax (query by value, patterns, value look-up in a lists, etc.). Here is an example of its syntax:

```
{“query”: {“Job”:re.compile(r”[a-z]+”, “X.Y.Z”:{“$in”:[1,2,3]}, …}
```

- For LTS we rely on HDFS+Spark and Map-Reduce paradigm
  - user provide business logic to search or aggregate the data, we wrap it up into Python Spark job
- Large data volume can be processed relatively fast:
  - search results across one **day** of data in ***O*(10) sec**, one **month** of data in ***O*(100) sec**

Benchmarks

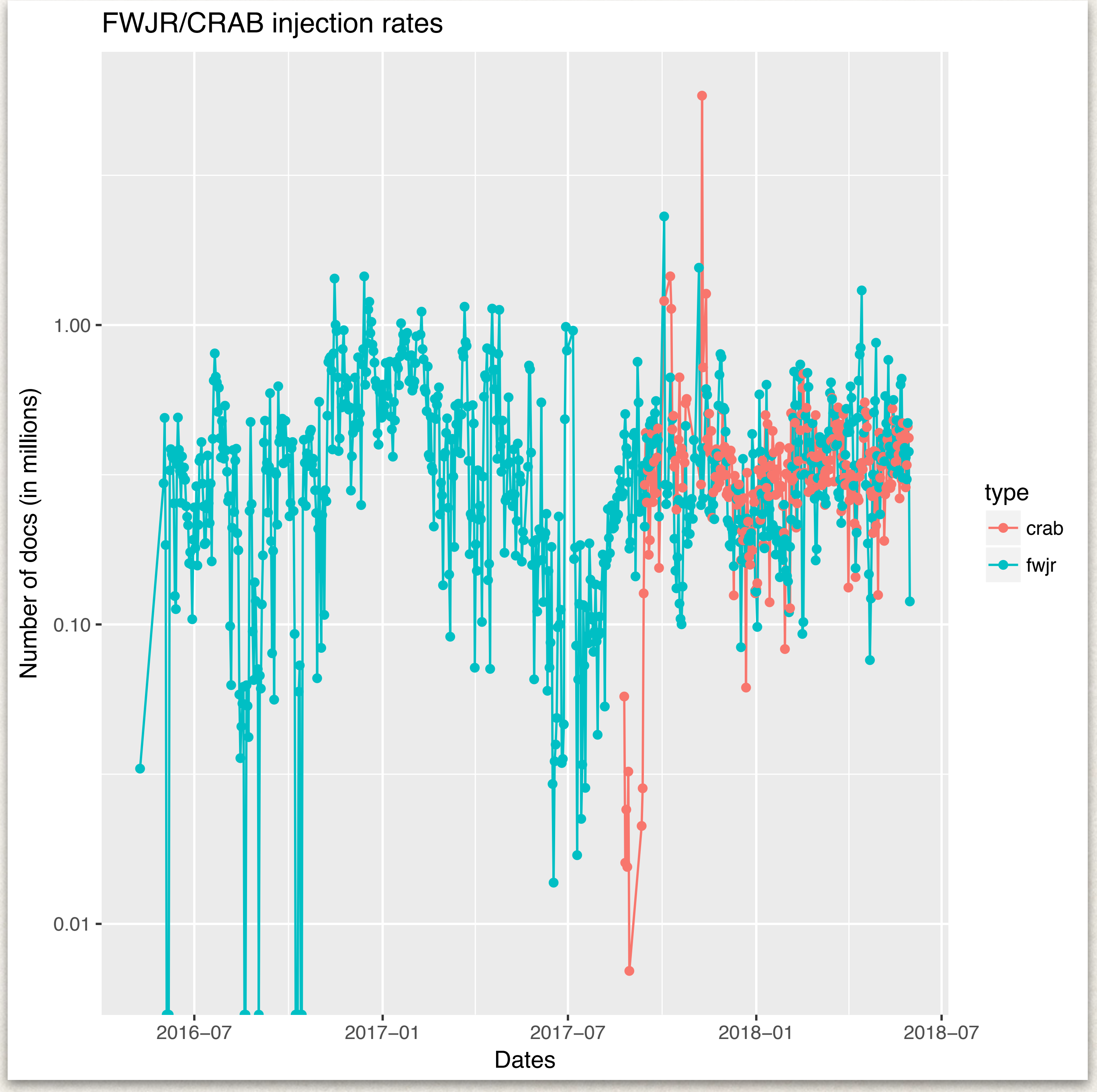
- STS: data injection rate 2KHz
  - 1.5M documents translates into 15GB database size with 3.5 GB of index size
- LTS: data look-up via Spark job
  - 1 day of data (200K docs) needs 1min, 2 month of data (12M docs) needs 1hour of processing time
- Single doc compression: JSON (**25KB**) ⇒ BSON (16KB) ⇒ Avro (7KB) ⇒ Avro.gz (**1KB**)
  - Multi-doc compression (use 10K docs): JSON (**250MB**) ⇒ BSON (160MB) ⇒ Avro (**70MB**) ⇒ Avro.bz2 (**352KB**)
- Final choice we store about 50-60K docs per single Avro to fit into 256MB block file constrain on HDFS

Current status

- The WMArchive system in production more than two year
  - one production and one testbed CERN VM (12 cores, 24GB RAM each)
- The data injection comes from 7 production WMAgent and 12 CRAB schedd nodes
- STS holds 3 months of data (tune-able parameter)
- We split STS/LTS into FWJR/CRAB collections
  - STS holds 2 separate collections for incoming docs and 2 collections for daily/hourly aggregated stats
    - each document has an internal state to indicate life-time of it in STS
- STS to LTS migration is done separately upon block completion (1 block contains ~60K docs and has 256MB size)

WMArchive data rate

- 7 production agents
- injection 24/7
    - 100k-1M docs per day
- docs migrated from STS to LTS once a day
- ~60k FWJR records per single (256MB) AVRO file
- Up-to-date we have 350M docs on HDFS (total size ~4TB)

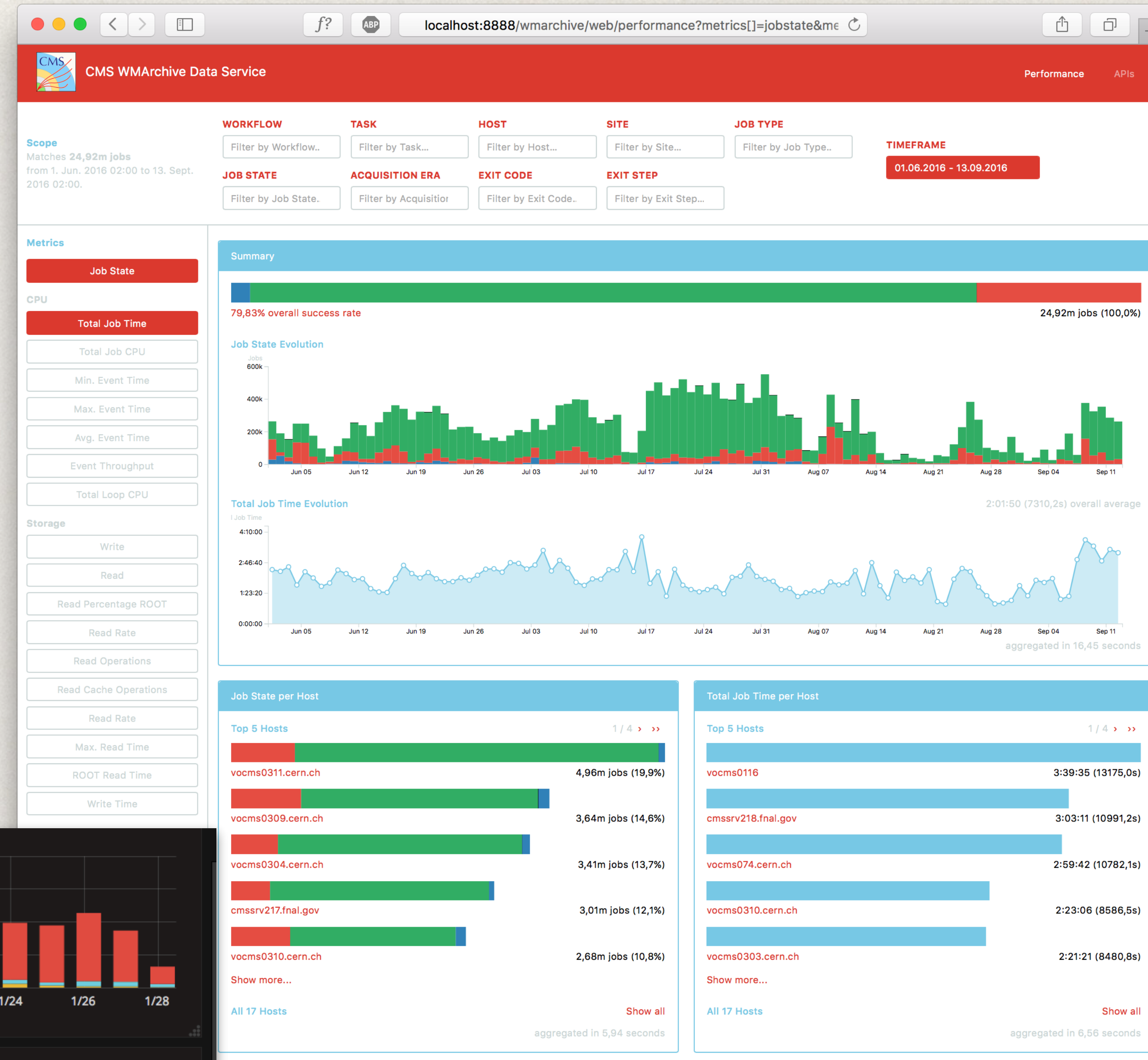


Use cases

- WMArchive is used on daily basis by data-ops to identify problems with running workflows
  - identify failed workflow
  - consult dashboard for problematic site
  - identify issues by log look-up and exit codes
- Monitoring CMS production status
  - sites, campaigns, throughput metrics
- Data aggregation use-cases

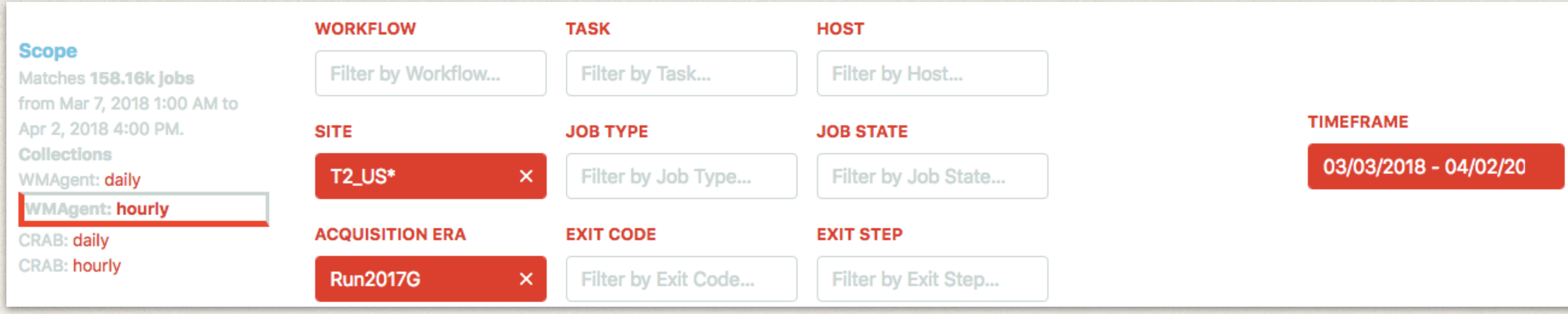
Custom UI was designed to address data-ops needs for fine-grained queries:

- job state evolution
- event throughput
- exit codes and states
- workflow monitoring
- CPU, Storage, Memory metrics

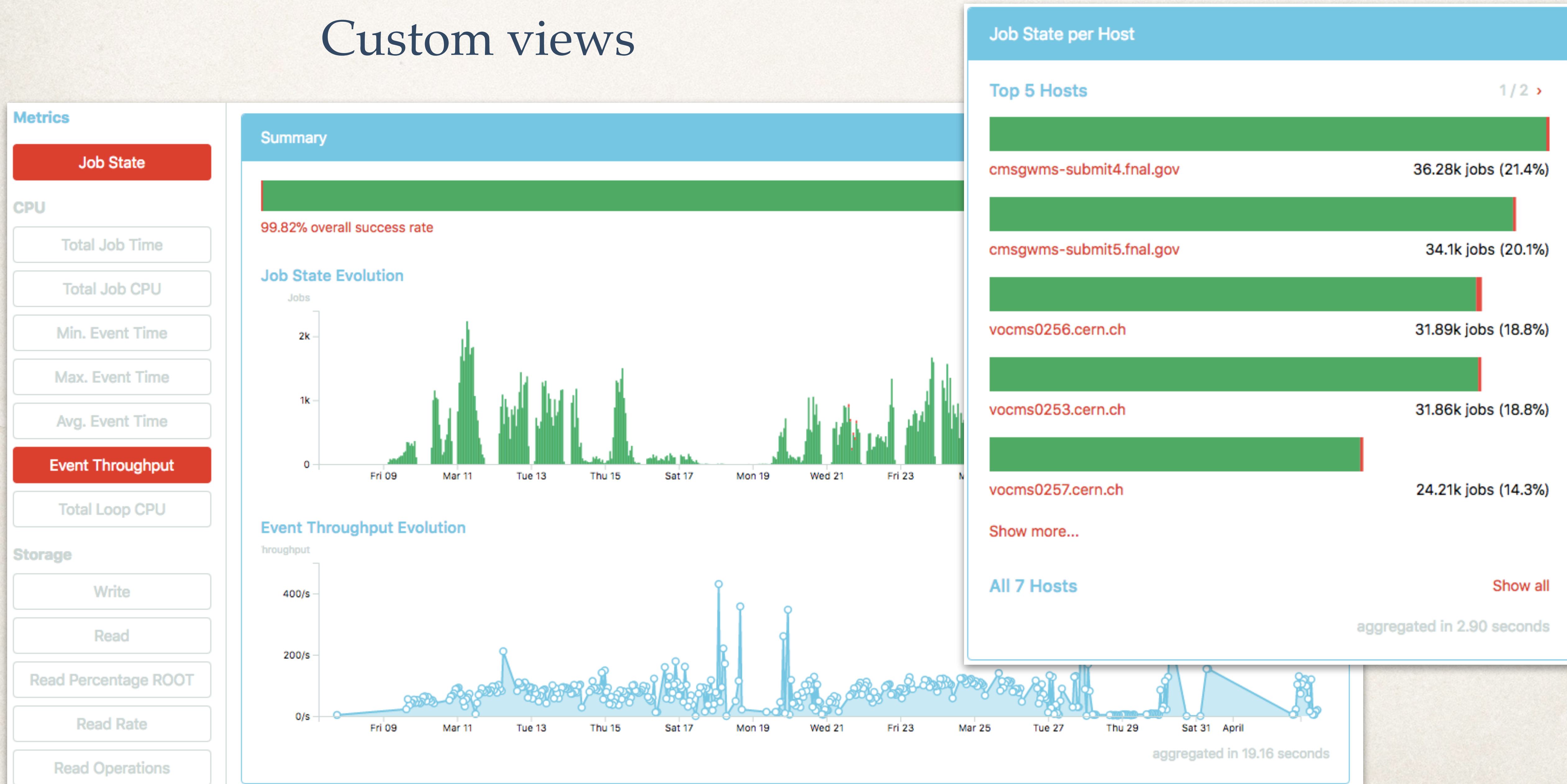


CERN MONIT dashboards provide global views of time series metrics

Custom cuts



Custom views



Example

- Find log files in **LTS** for specific job/LFN while investigating failing workflows
  - very cumbersome operation and require multi-pass operation look-up in WMArchive document store
    - file resolution (which file belong to which processing chain step)
    - look-up log archive and log collect steps
    - input/output file matching
- User provides a JSON file with input parameters

```
{"spec":{"lfn":"file.root", "timerange":[20180502,20180520]}}
```

- Run spark job to process O(M) documents, data-look-up time ~ few minutes
  - we provide custom Map-Reduce code to perform this task efficiently on Spark platform
  - results show location of tar-ball on EOS

Summary

- WMArchive consists of loosely coupled layers for meta-data storage and archiving
  - we used different technologies to accommodate high-injection rate, schema evolution, large data-volume, flexible QL and search capabilities
  - custom UI along with global dashboards satisfies data-ops needs
  - in 2 years we accumulated 300M docs and will hit 1B in HL-LHC era
  - we didn’t experience any issues during production operation and run service on a single node
- WMArchive opens up possibilities to study users patterns and predict users behavior
  - it is part of larger effort in CMS to study resource utilization, see more in ***Gaining Insight From Large Data Volumes with Ease*** poster by Valentin Kuznetsov