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아파치 스팍
통합 경험기

DEVIEW
2015

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소속: 넷플릭스

NETFLIX

Outline

1. Netflix big data platform
2. Spark @ Netflix
3. Dynamic allocation
4. Predicate pushdown
5. S3 file listing
6. S3 insert overwrite
7. Zeppelin, Ipython notebooks
8. Use case (Pig vs. Spark)

Netflix
Big Data Platform

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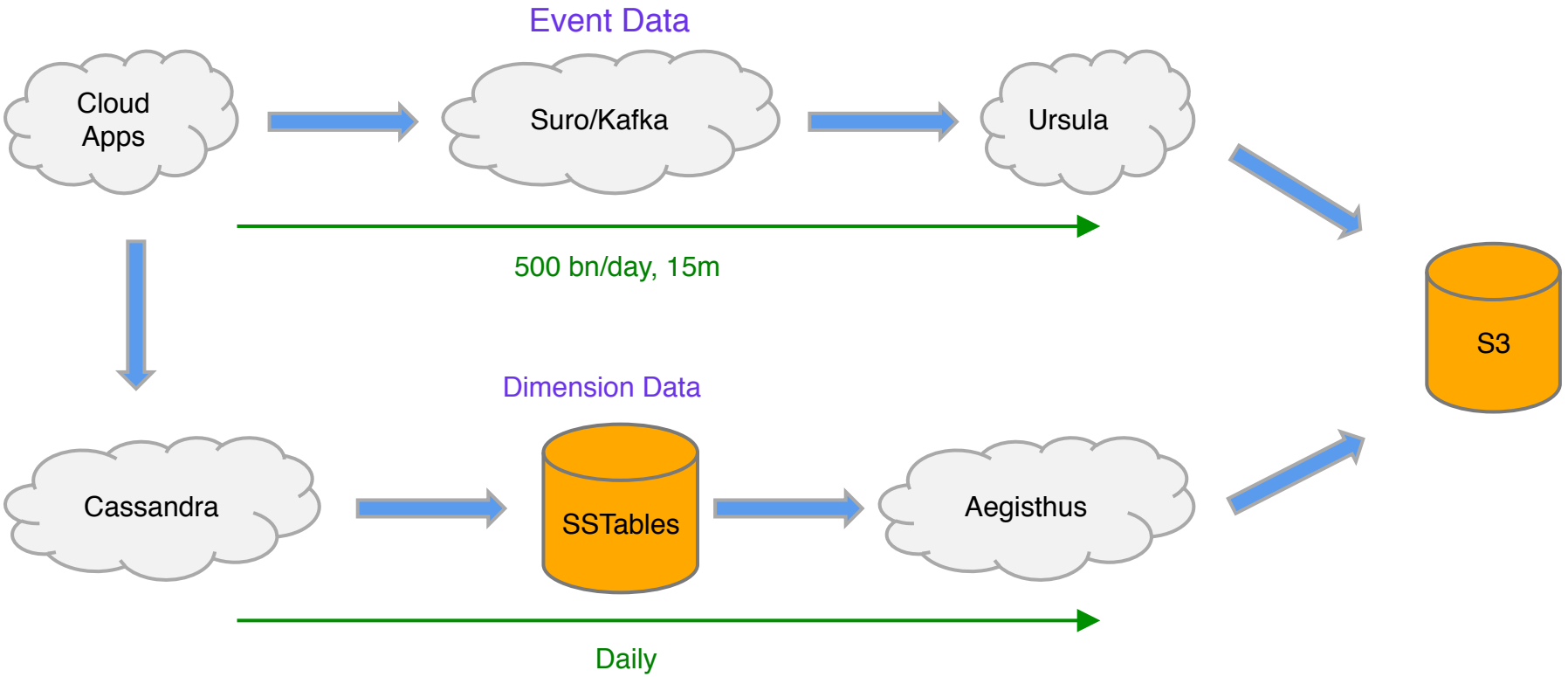
Netflix data pipeline



Netflix big data platform

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Tools — **Big Data API/Portal** — 

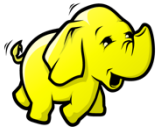
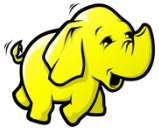
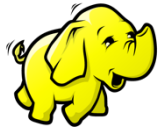
Service — 

Metacat

Gateways — 

Clients — 



Clusters — 


Prod Test Adhoc

Prod Test

Data Warehouse — 

Our use cases

- Batch jobs (Pig, Hive)
  - ETL jobs
  - Reporting and other analysis
- Interactive jobs (Presto)
- Iterative ML jobs (Spark)

Spark @ Netflix

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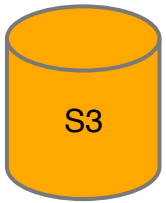
Mix of deployments

- Spark on Mesos
  - Self-serving AMI
  - Full BDAS (**B**erkeley **D**ata **A**nalytics **S**tack)
  - Online streaming analytics
- Spark on YARN
  - Spark as a service
  - YARN application on EMR Hadoop
  - Offline batch analytics

Spark on YARN

- Multi-tenant cluster in AWS cloud
  - Hosting MR, Spark, Druid
- EMR Hadoop 2.4 (AMI 3.9.0)
- D2.4xlarge ec2 instance type
- 1000+ nodes (100TB+ total memory)

Deployment



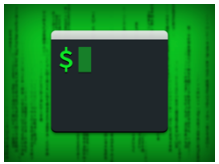
s3://bucket/spark/1.4/spark-1.4.tgz, spark-defaults.conf (spark.yarn.jar=1440304023)

s3://bucket/spark/1.5/spark-1.5.tgz, spark-defaults.conf (spark.yarn.jar=1440443677)

/spark/1.4/1440304023/spark-assembly.jar
/spark/1.4/1440989711/spark-assembly.jar

/spark/1.5/1440443677/spark-assembly.jar
/spark/1.5/1440720326/spark-assembly.jar


```
name: spark
version: 1.5
tags: ['type:spark', 'ver:1.5']
jars:
    - 's3://bucket/spark/1.5/spark-1.5.tgz'
```



Download latest tarball
From S3 via Genie

Goals

1. Automate deployment.
2. Support multiple versions.
3. Deploy new code in 15 minutes.
4. Roll back bad code in less than a minute.

Dynamic Allocation

Dynamic allocation

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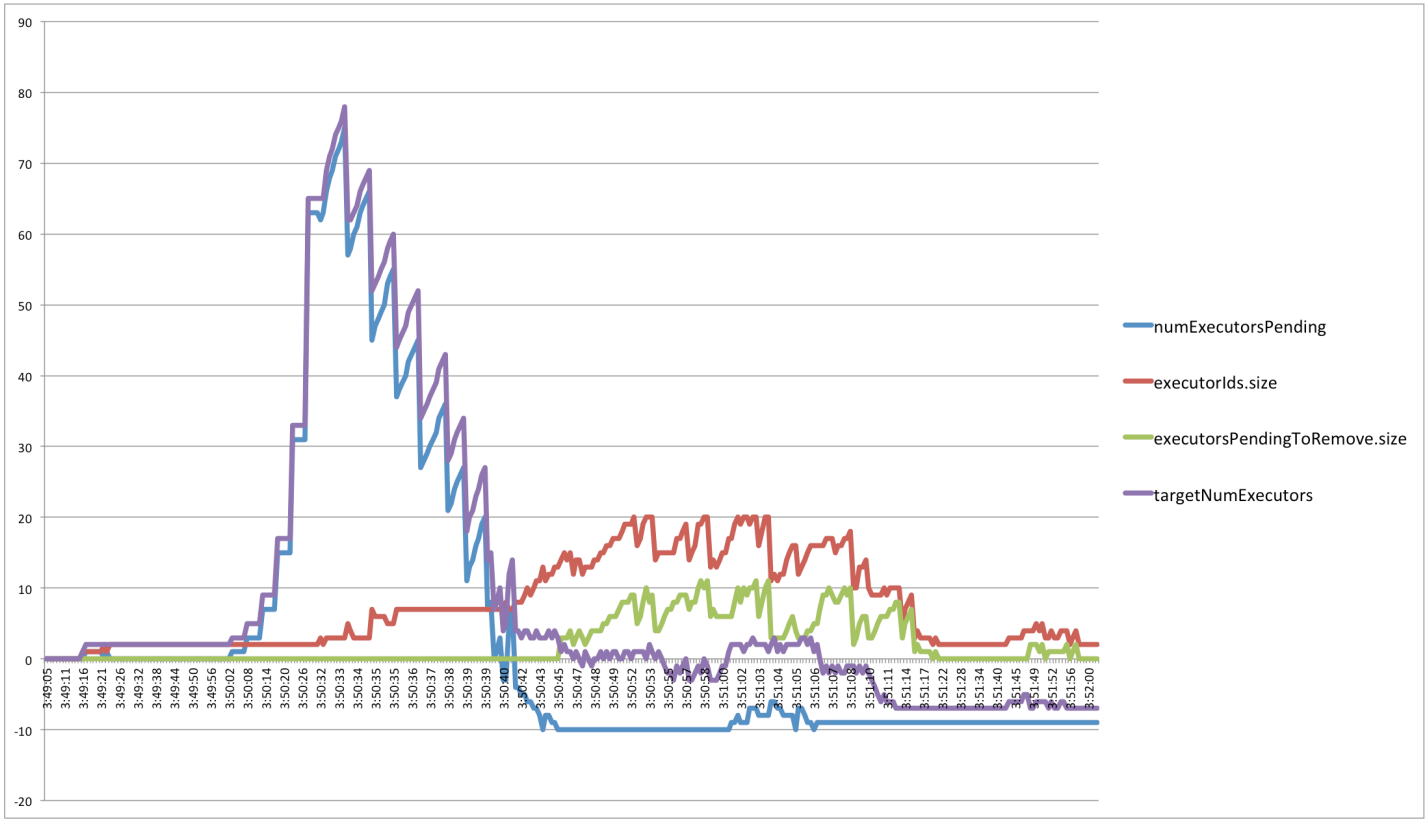
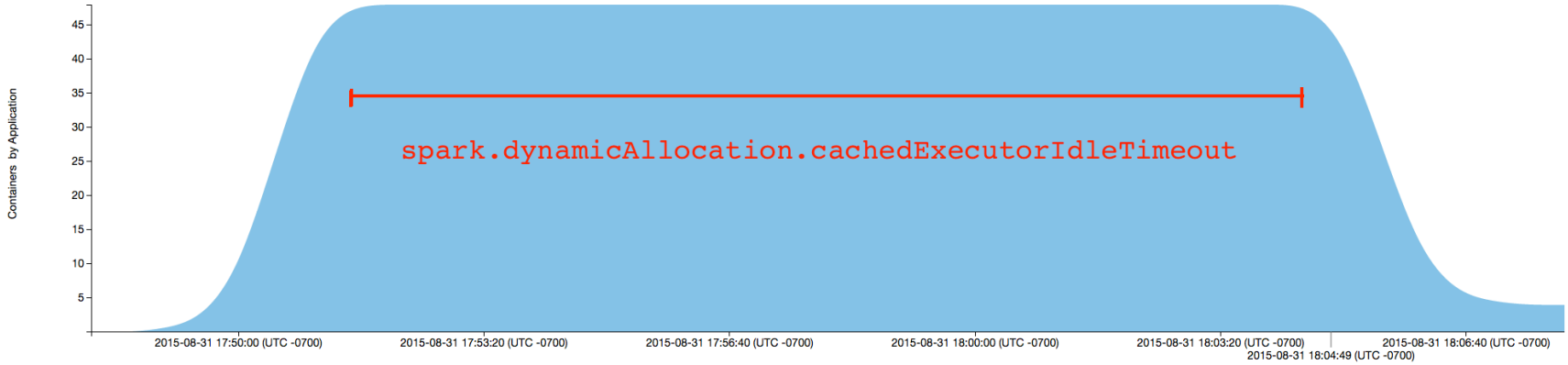
```
// spark-defaults.conf
spark.dynamicAllocation.enabled                          true
spark.dynamicAllocation.executorIdleTimeout              5
spark.dynamicAllocation.initialExecutors                 3
spark.dynamicAllocation.maxExecutors                     500
spark.dynamicAllocation.minExecutors                     3
spark.dynamicAllocation.schedulerBacklogTimeout          5
spark.dynamicAllocation.sustainedSchedulerBacklogTimeout 5
spark.dynamicAllocation.cachedExecutorIdleTimeout        900
```

```
// yarn-site.xml
yarn.nodemanager.aux-services
    • spark_shuffle, mapreduce_shuffle
yarn.nodemanager.aux-services.spark_shuffle.class
    • org.apache.spark.network.yarn.YarnShuffleService
```

SPARK-6954


90
80
70
60
50
40
30
20
10
0
-10
-20
numExecutorsPending
executorIds.size
executorsPendingToRemove.size
targetNumExecutors

SPARK-7955




```
val data = sqlContext
    .table("dse.admin_genie_job_d”)
    .filter($"dateint">=20150601 and $"dateint"<=20150830)
data.persist
data.count
```

SPARK-8167

- Symptom
  - Spark tasks randomly fail with “executor lost” error.
- Cause
  - YARN preemption is not graceful.
- Solution
  - Preempted tasks shouldn’t be counted as failures but should be retried.

YARN-2730

- Symptom
  - MR jobs get timed out during localization when running with Spark jobs on the same cluster.
- Cause
  - NM localizes one job at a time. Since Spark runtime jar is big, localizing Spark jobs may take long, blocking MR jobs.
- Solution
  - Stage Spark runtime jar on HDFS with high repliacation.
  - Make NM localize multiple jobs concurrently.

Predicate Pushdown

Predicate pushdown

Case	Behavior
Predicates with partition cols on partitioned table	Single partition scan
Predicates with partition and non-partition cols on partitioned table	Single partition scan
No predicate on partitioned table e.g. sqlContext.table(“nccp_log”).take(10)	Full scan
No predicate on non-partitioned table	Single partition scan

Predicate pushdown for metadata

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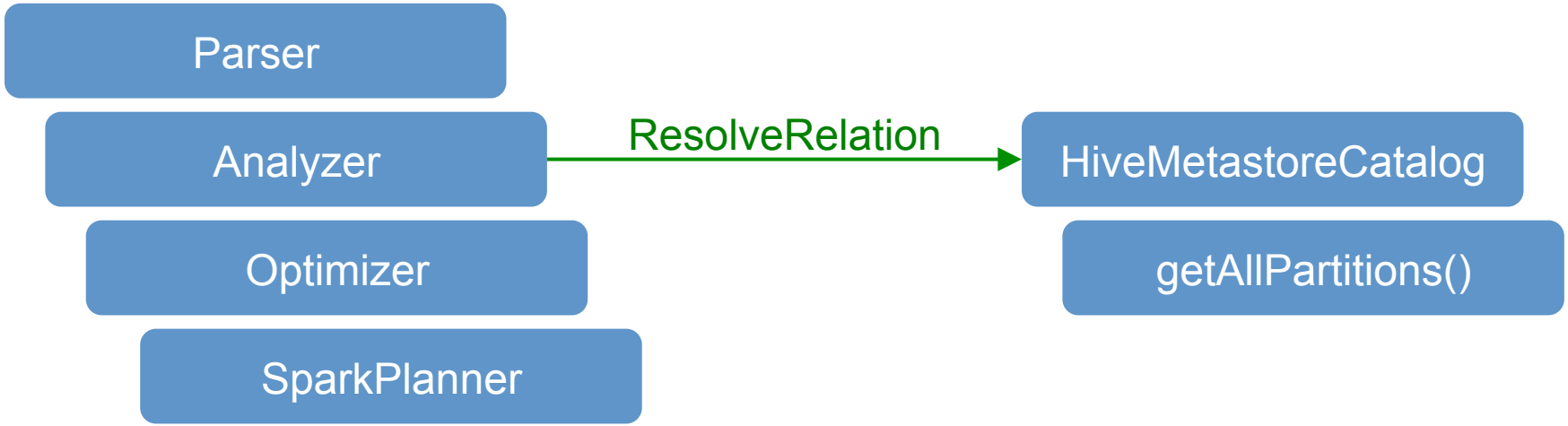
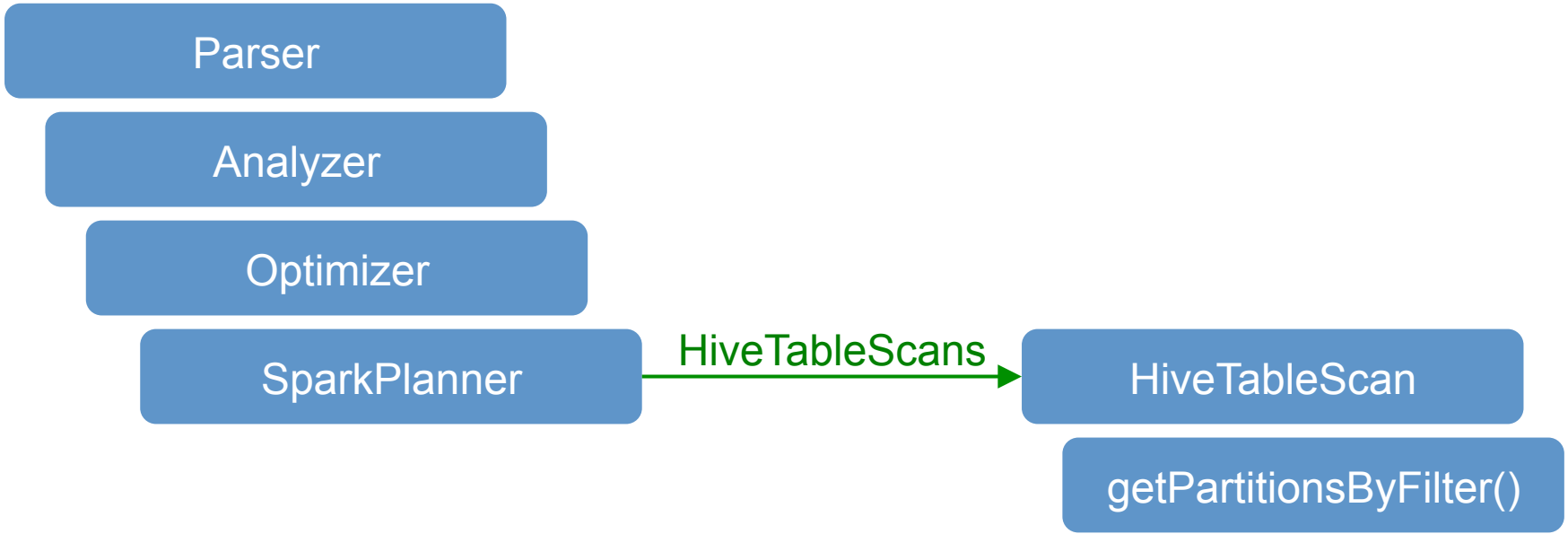


What if your table has 1.6M partitions?

SPARK-6910

- Symptom
  - Querying against heavily partitioned Hive table is slow.
- Cause
  - Predicates are not pushed down into Hive metastore, so Spark does full scan for table metadata.
- Solution
  - Push down binary comparison expressions via getPartitionsByfilter() in to Hive metastore.

Predicate pushdown for metadata



S3
File Listing

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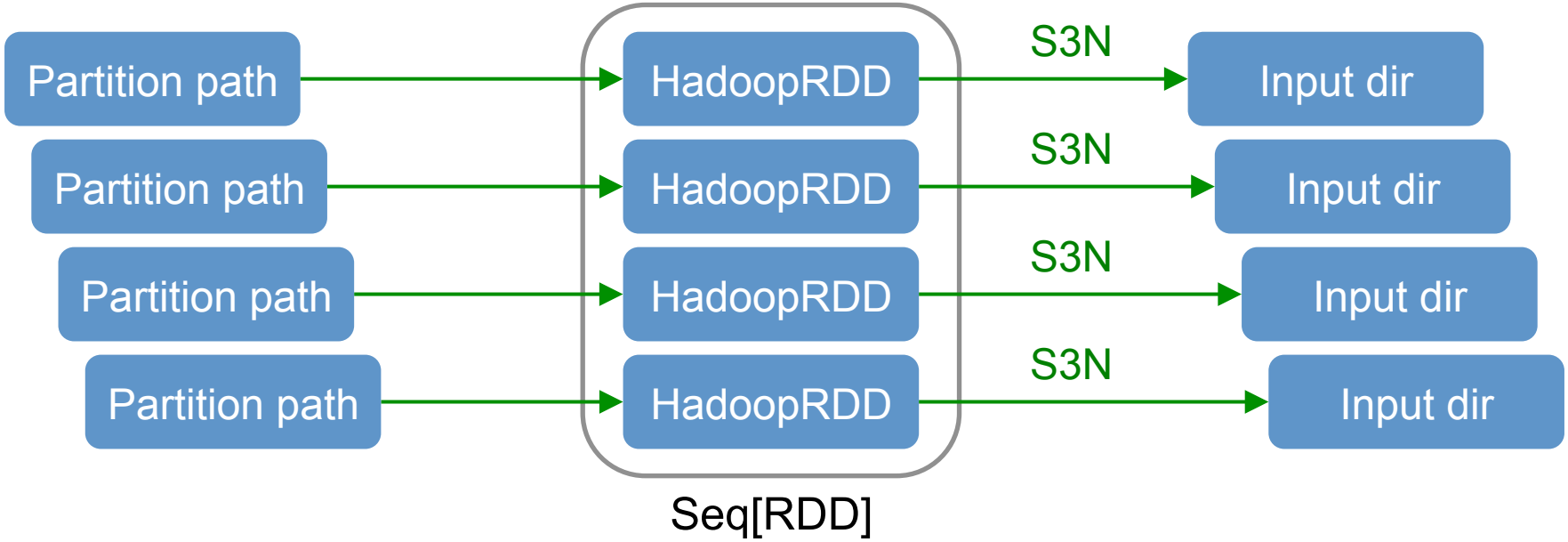
Input split computation

- mapreduce.input.fileinputformat.list-status.num-threads
  - The number of threads to use list and fetch block locations for the specifi ed input paths.
- Setting this property in Spark jobs doesn't help.

File listing for partitioned table

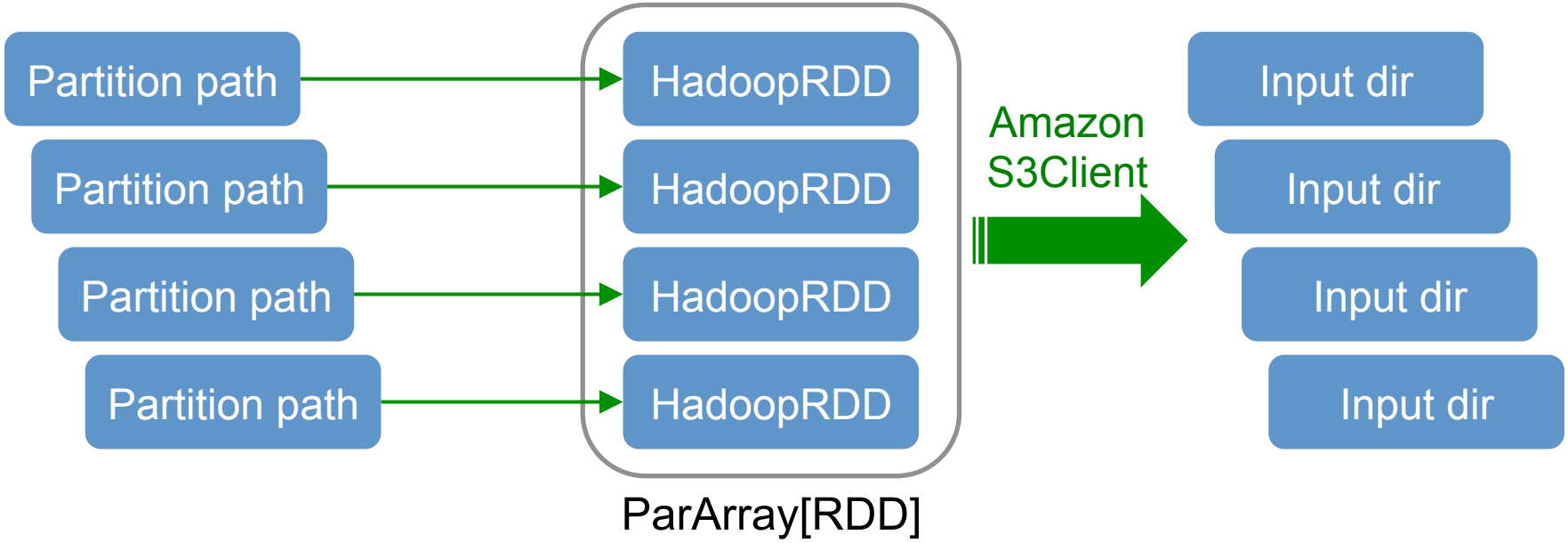


Sequentially listing input dirs via S3N file system.

SPARK-9926, SPARK-10340

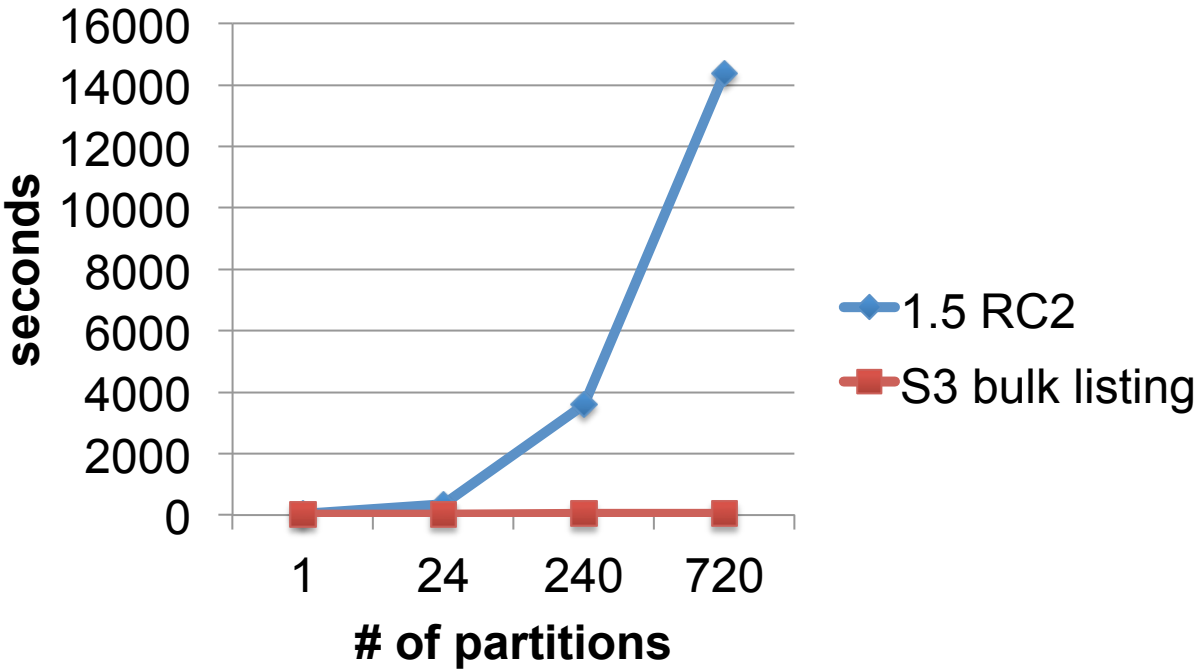
- Symptom
  - Input split computation for partitioned Hive table on S3 is slow.
- Cause
  - Listing files on a per partition basis is slow.
  - S3N file system computes data locality hints.
- Solution
  - Bulk list partitions in parallel using AmazonS3Client.
  - Bypass data locality computation for S3 objects.

S3 bulk listing



Bulk listing input dirs in parallel via AmazonS3Client.

Performance improvement




```
SELECT * FROM nccp_log WHERE dateint=20150801 and hour=0 LIMIT 10;
```

S3
Insert Overwrite

Hadoop output committer

- How it works:
  - Each task writes output to a temp dir.
  - Output committer renames first successful task's temp dir to fin al destination.
- Problems with S3:
  - S3 rename is copy and delete.
  - S3 is eventual consistent.
  - FileNotFoundException during "rename."

S3 output committer

- How it works:
  - Each task writes output to local disk.
  - Output committer copies first successful task's output to S3.
- Advantages:
  - Avoid redanant S3 copy.
  - Avoid eventual consistency.

Hive insert overwrite

- How it works:
  - Delete and rewrite existing output in partitions.
- Problems with S3:
  - S3 is eventual consistent.
  - FileAlreadyExistException during “rewrite.”

Batchid pattern

- How it works:
  - Never delete existing output in partitions.
  - Each job inserts a unique subpartition called “batchid.”
- Advantages:
  - Avoid eventual consistency.

Zeppelin Ipython Notebooks

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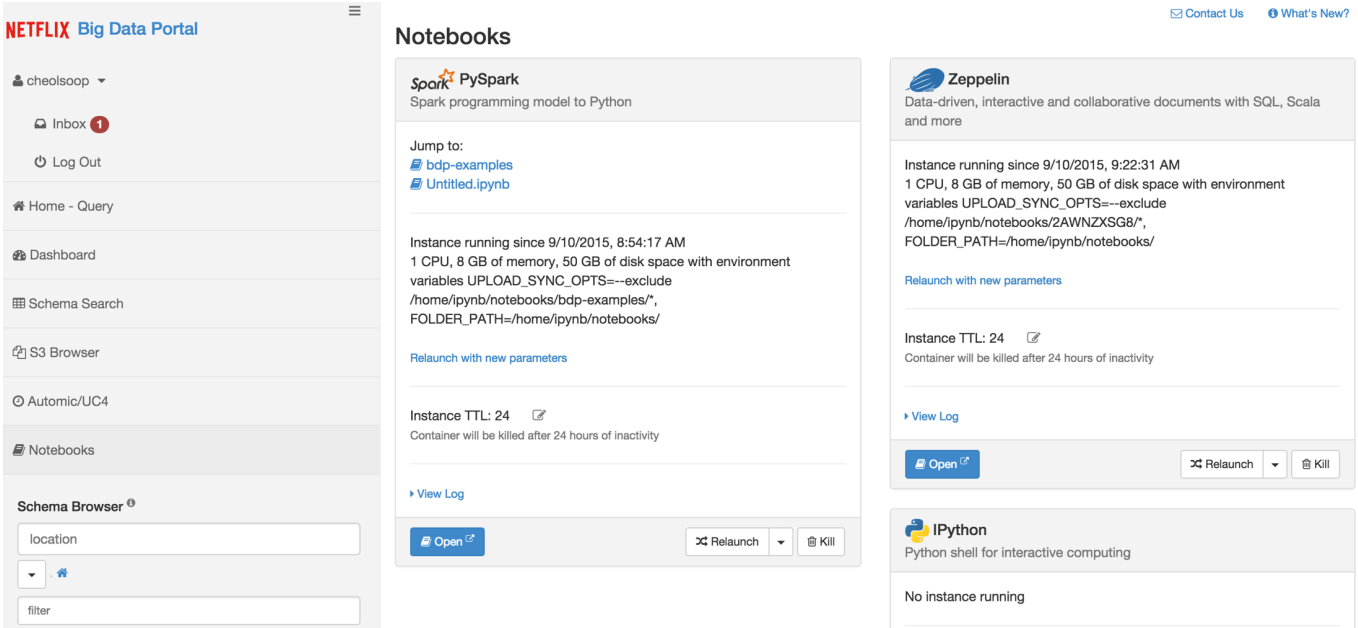
Big data portal

- One stop shop for all big data related tools and services.
- Built on top of Big Data API.



Out of box examples

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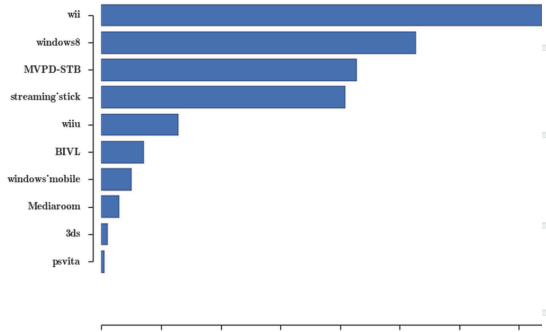
jupyter PySparkExamples (read only)

File Edit View Insert Cell Kernel Help | Python 2

Code | Cell Toolbar: None

In [20]:
```
# Quick visualization
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

sns.set_context('talk')
sns.set_style("white")
sns.set_style("ticks")
device, streams = zip(*top10)
ypos = np.arange(len(top10))
plt.barh(ypos, streams, align='center')
plt.yticks(ypos, device)
sns.despine(offset=10, trim=True)
```



Zeppelin Notebook Interpreter Connected

Save Cancel

```
// What are the most popular titles on Netflix? Let's start by querying some play data for 1 day
val plays = sqlContext.sql("select profile_id, country_iso_code, standard_sanitized_duration_sec/3600 as play_hrs, show_title_id from dse.loc_acct_device_ttl_sum where region_date=20150601
)
// Now group it by country and show
// How do we quantify popularity ?
// -- number of plays?
// -- number of users?
// -- number of hours?
// Let's try all three and compare
```

FINISHED

```
popularity.filter(popularity("country_iso_code")==="US").orderBy(popularity("SUM(play_hrs)").desc).take(25)
// you can also reference columns with the $ operator
popularity.filter(popularity("country_iso_code")==="US").orderBy(popularity("APPROXIMATE COUNT(DISTINCT profile_id)").desc).take(25)
popularity.filter(popularity("country_iso_code")==="US").orderBy(popularity("COUNT(profile_id)").desc).take(25)
```

FINISHED

```
// notice that the query has to recompute the data each time ... so let's persist our intermediate "popularity" variable
popularity.persist()
```

res28: popularity.type = [country_iso_code: string, show_title_id: int, SUM(play_hrs): double, APPROXIMATE COUNT(DISTINCT profile_id): bigint, COUNT(profile_id): bigint]

Took 1 seconds

FINISHED

```
// We can't really tell what the titles are b/c they only have an id. Let's join or popularity to some title metadata
val titles = sqlContext.table("dse.ttl_show_d")
val popularity_metadata = popularity.join(titles,titles("show_title_id")===popularity("show_title_id"))
popularity_metadata.filter(popularity_metadata("country_iso_code")==="US").orderBy(popularity_metadata("SUM(play_hrs)").desc).take(25)
```

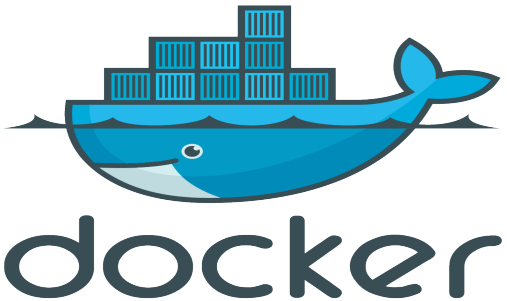
FINISHED

```
// The display still is ugly, let's use Zeppelin's markup to display this as a table:
print(s"""%table
country_iso_code\tshow_desc\tcontent_type\tgenre\tplay_hours\tnumber_profiles\tnumber_plays
""")
popularity_metadata.orderBy(popularity_metadata("SUM(play_hrs)").desc).take(10000).foreach(line => println(s"""""+line(0)+s"""\t"""+line(6)+s"""\t"""+line(17)+s"""\t"""+line(13)+s"""\t"""
```

FINISHED

On demand notebooks

- Zero installation
  - Dependency management via Docker
- Notebook persistence
- Elastic resources



Notebook Infrastructure

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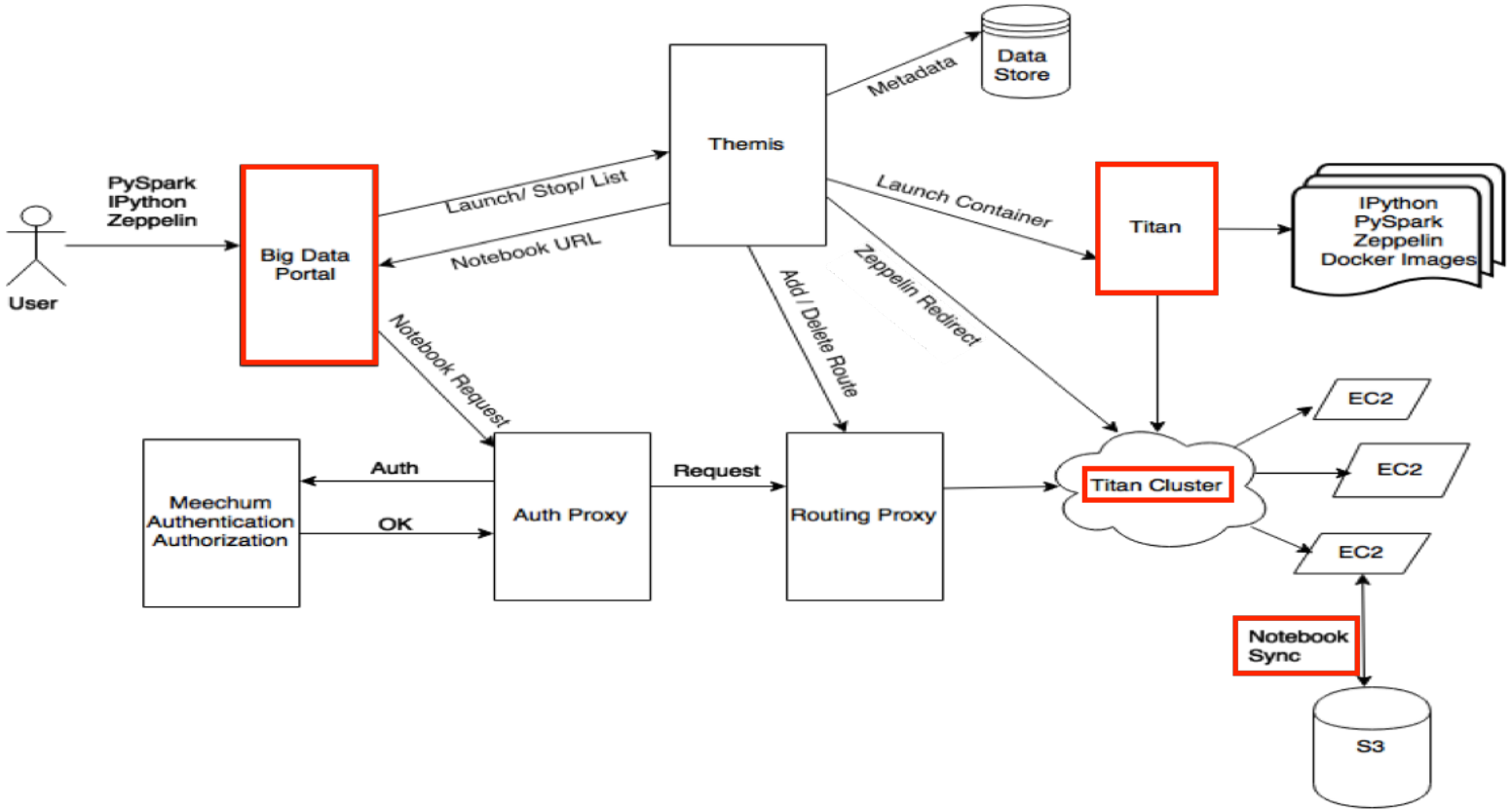
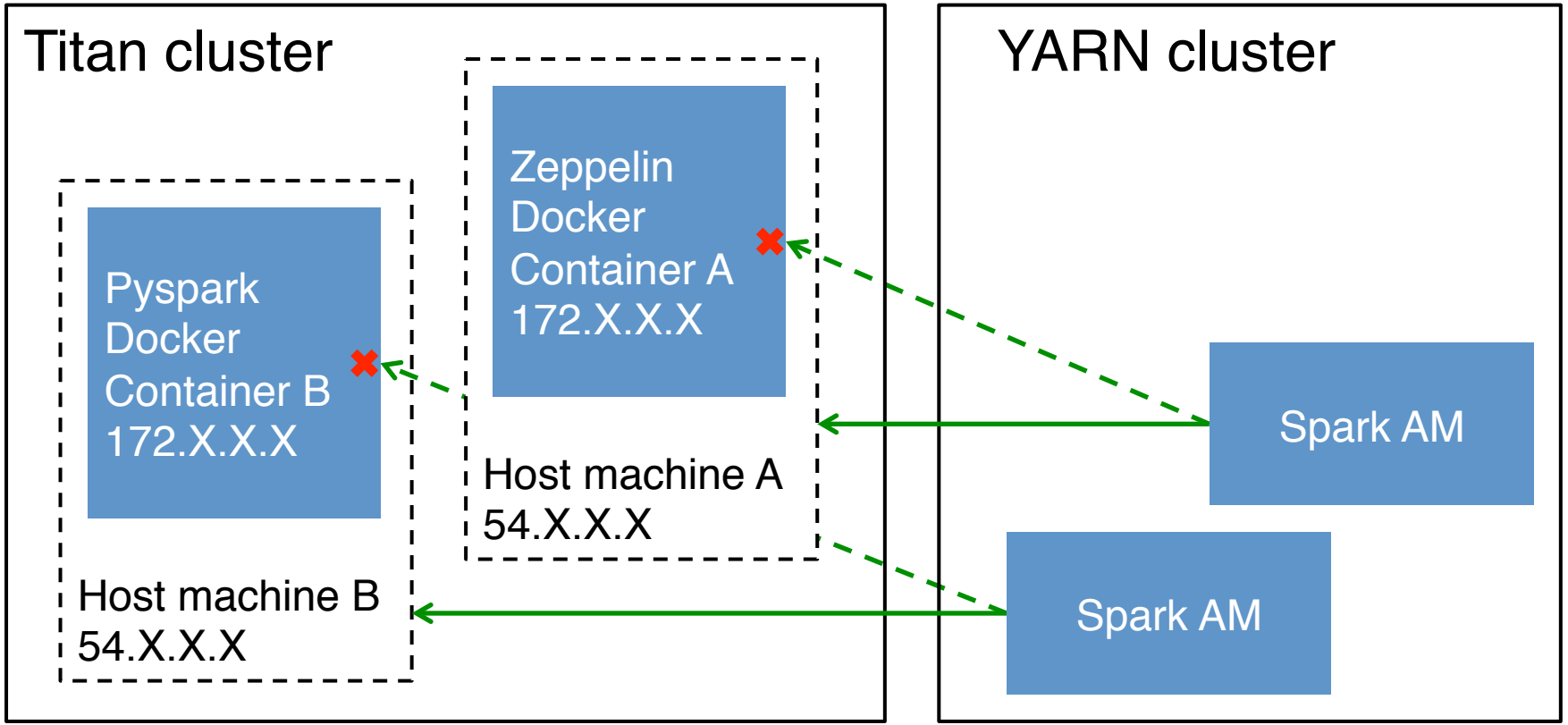


Quick facts about Titan

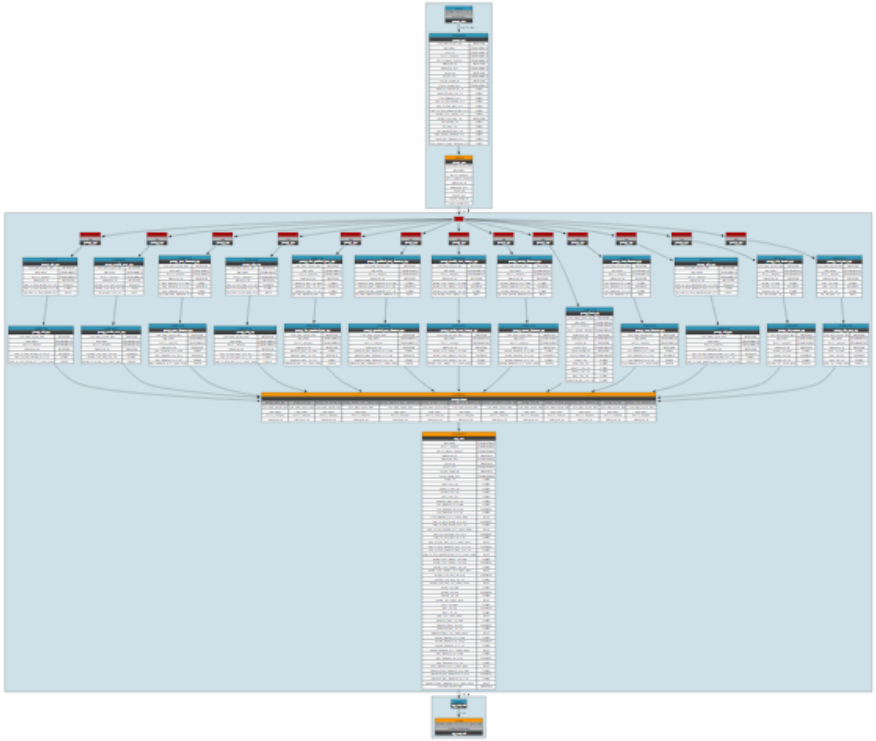
- Task execution platform leveraging Apache Mesos.
- Manages underlying EC2 instances.
- Process supervision and uptime in the face of failures.
- Auto scaling.

Ephemeral ports / --net=host mode

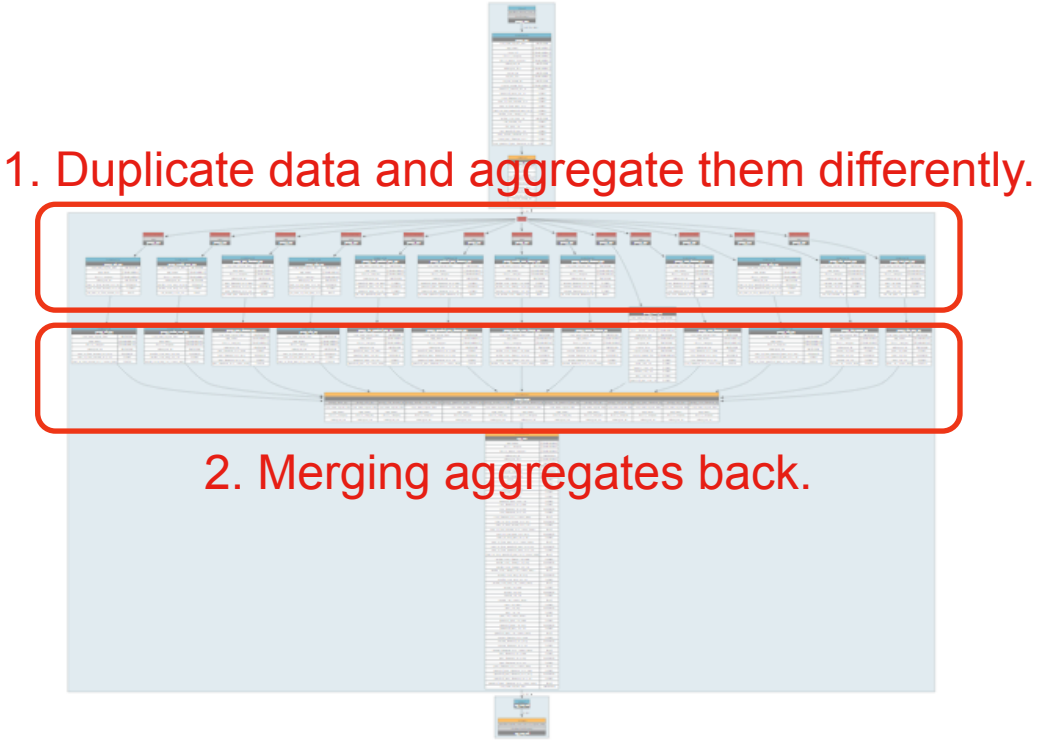


Use Case
Pig vs. Spark

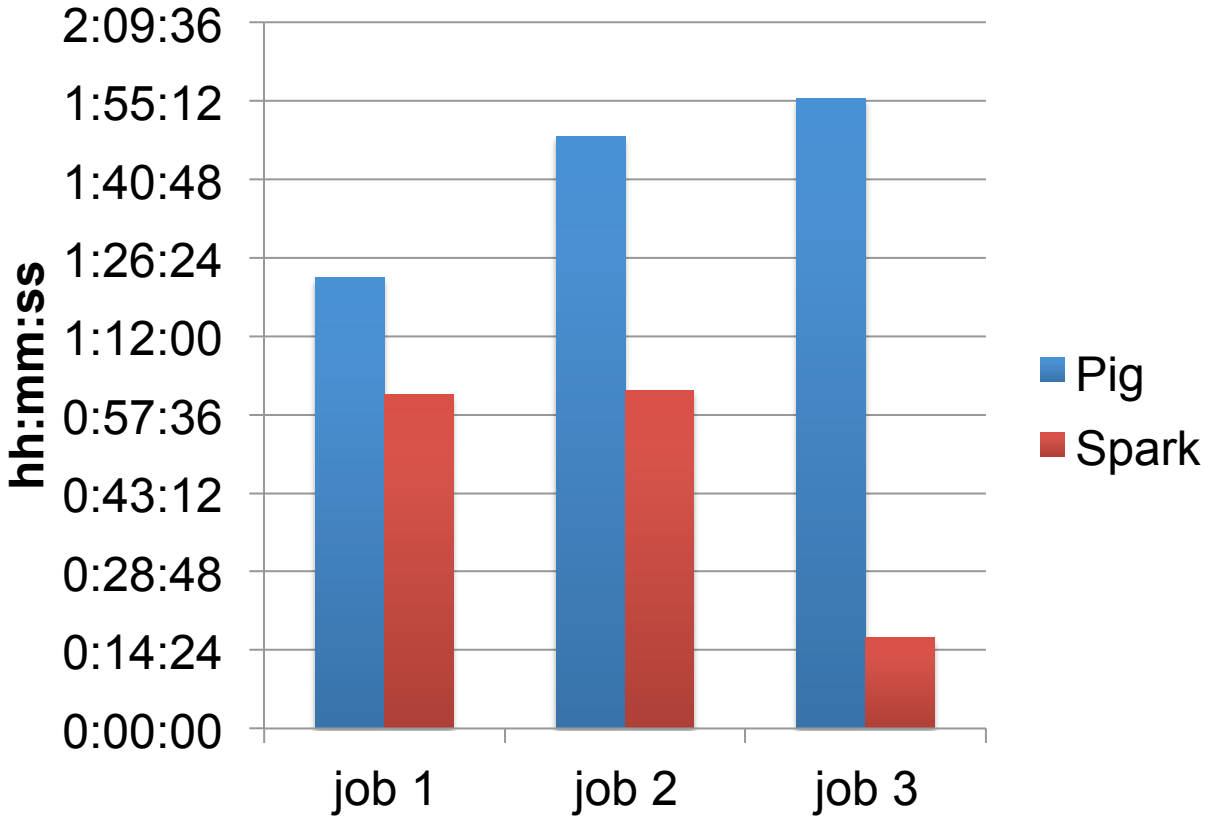
Iterative job



Iterative job



Performance improvement



Our contributions

SPARK-6018
SPARK-6662
SPARK-6909
SPARK-6910
SPARK-7037
SPARK-7451
SPARK-7850
SPARK-8355
SPARK-8572
SPARK-8908
SPARK-9270
SPARK-9926
SPARK-10001
SPARK-10340

Q&A

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Thank You