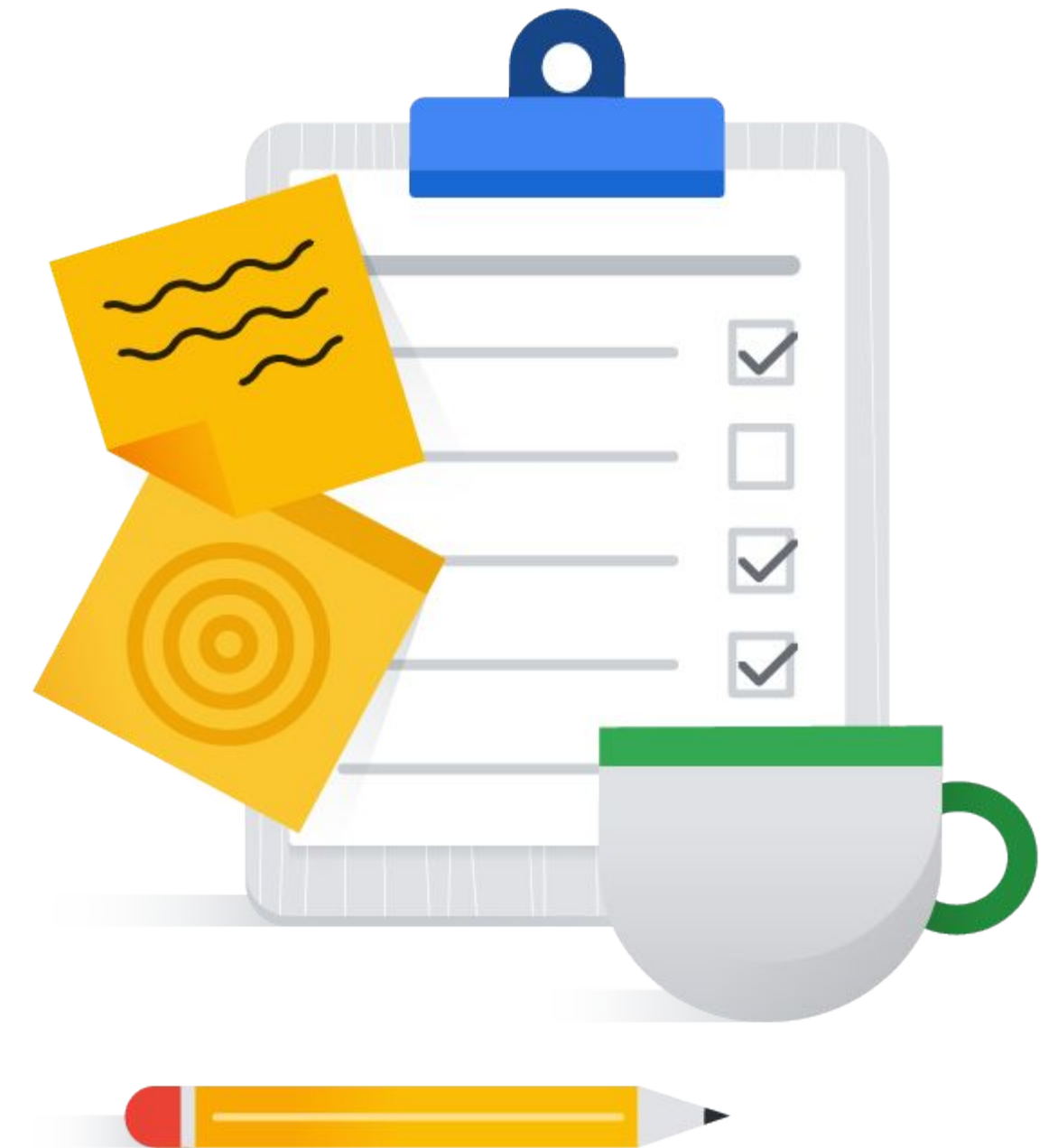




# Executing Spark on Dataproc

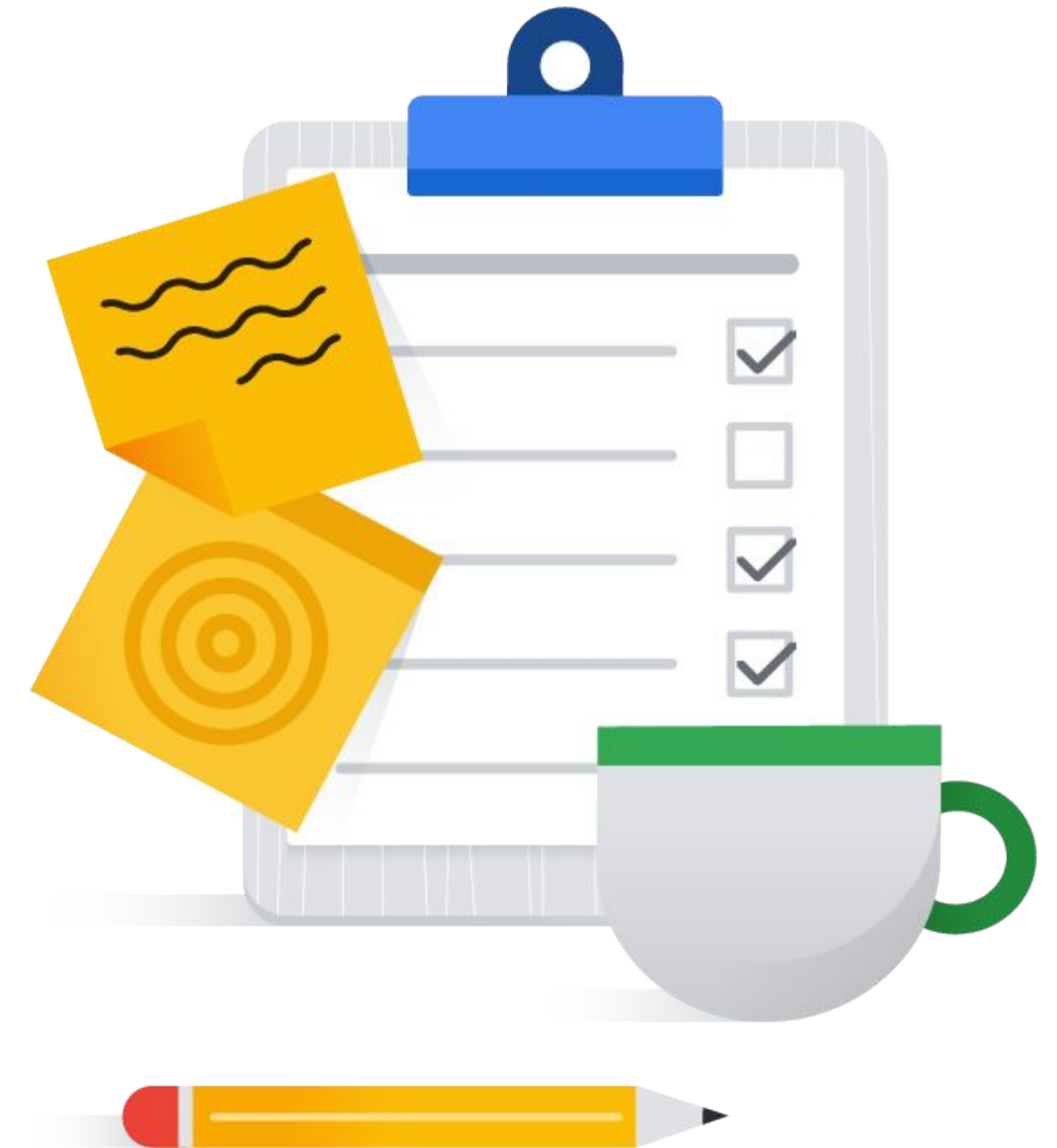
# Executing Spark on Dataproc

01	The Hadoop Ecosystem
02	Running Hadoop on Dataproc
03	Cloud Storage Instead of HDFS
04	Optimizing Dataproc

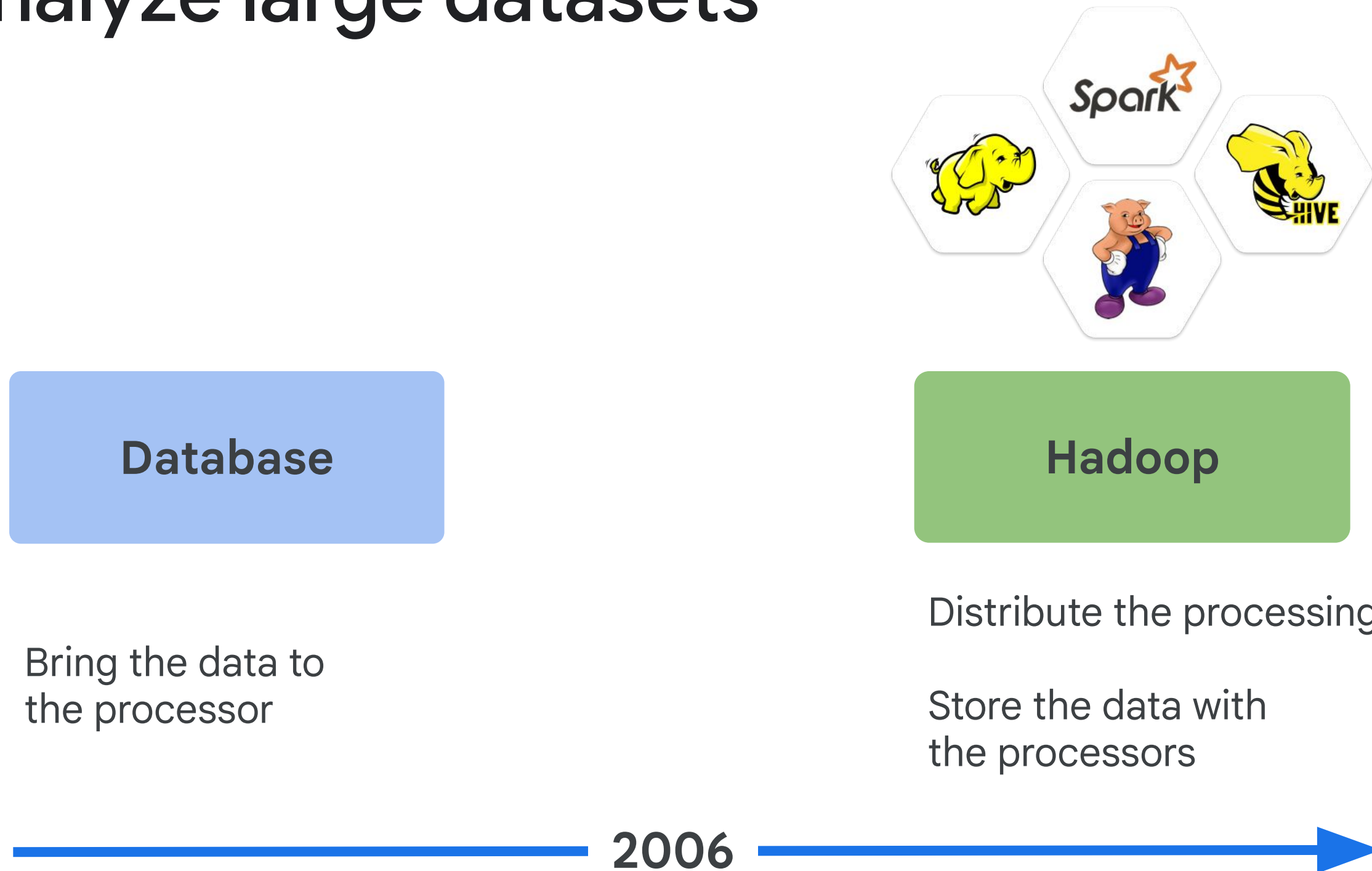


# Executing Spark on Dataproc

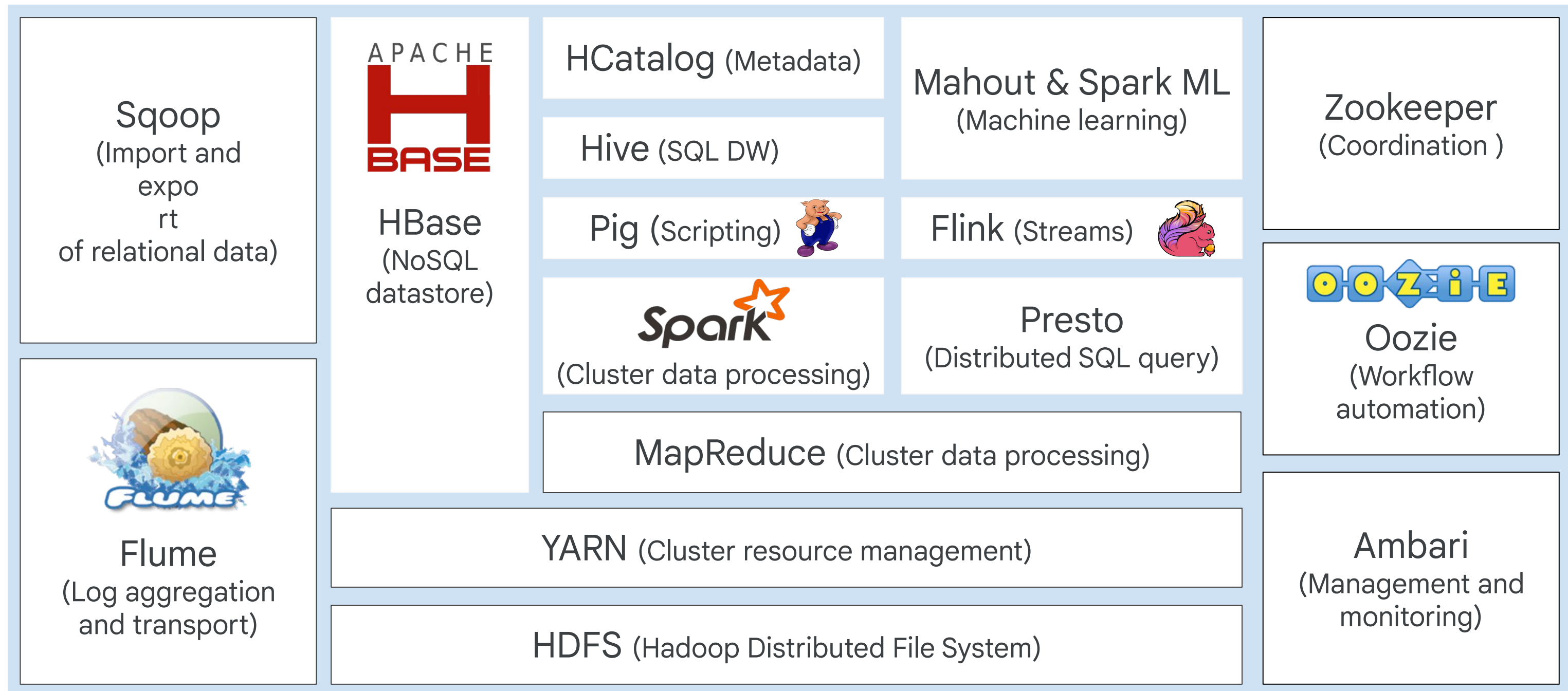
01	The Hadoop ecosystem
02	Running Hadoop on Dataproc
03	Cloud Storage instead of HDFS
04	Optimizing Dataproc




# The Hadoop ecosystem developed because of a need to analyze large datasets





# The Hadoop ecosystem is very popular for Big Data workloads



# On-premises Hadoop clusters are not elastic

 No separation between storage and compute resources

 Hard to scale fast

 Capacity limits

# Dataproc simplifies Hadoop workloads on Google Cloud

- ✓ Built-in support for Hadoop
- ✓ Managed hardware and configuration
- ✓ Simplified version management
- ✓ Flexible job configuration

# Apache Spark is a popular, flexible, powerful way to process large datasets



etc.

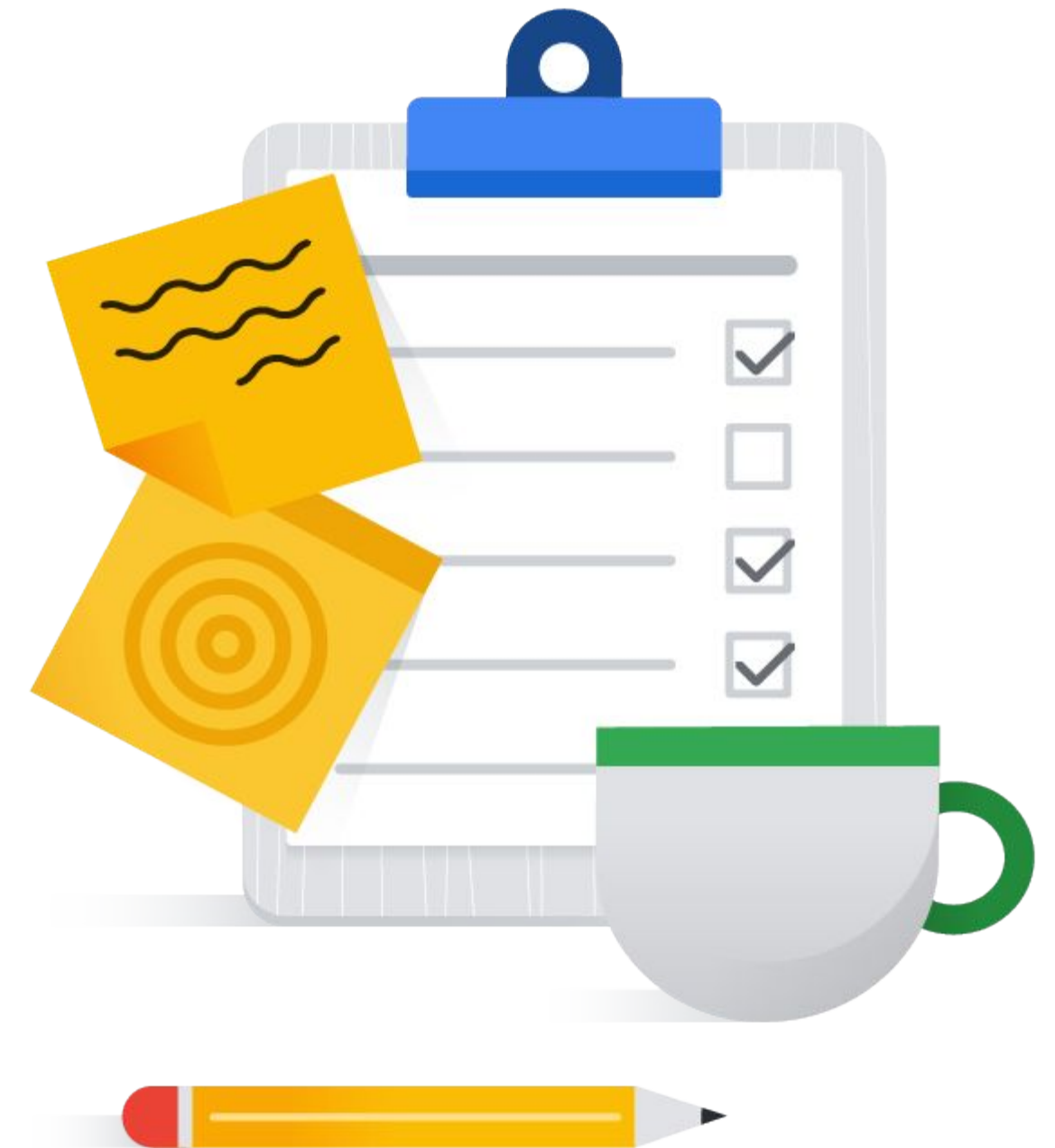


[spark.apache.org](https://spark.apache.org)



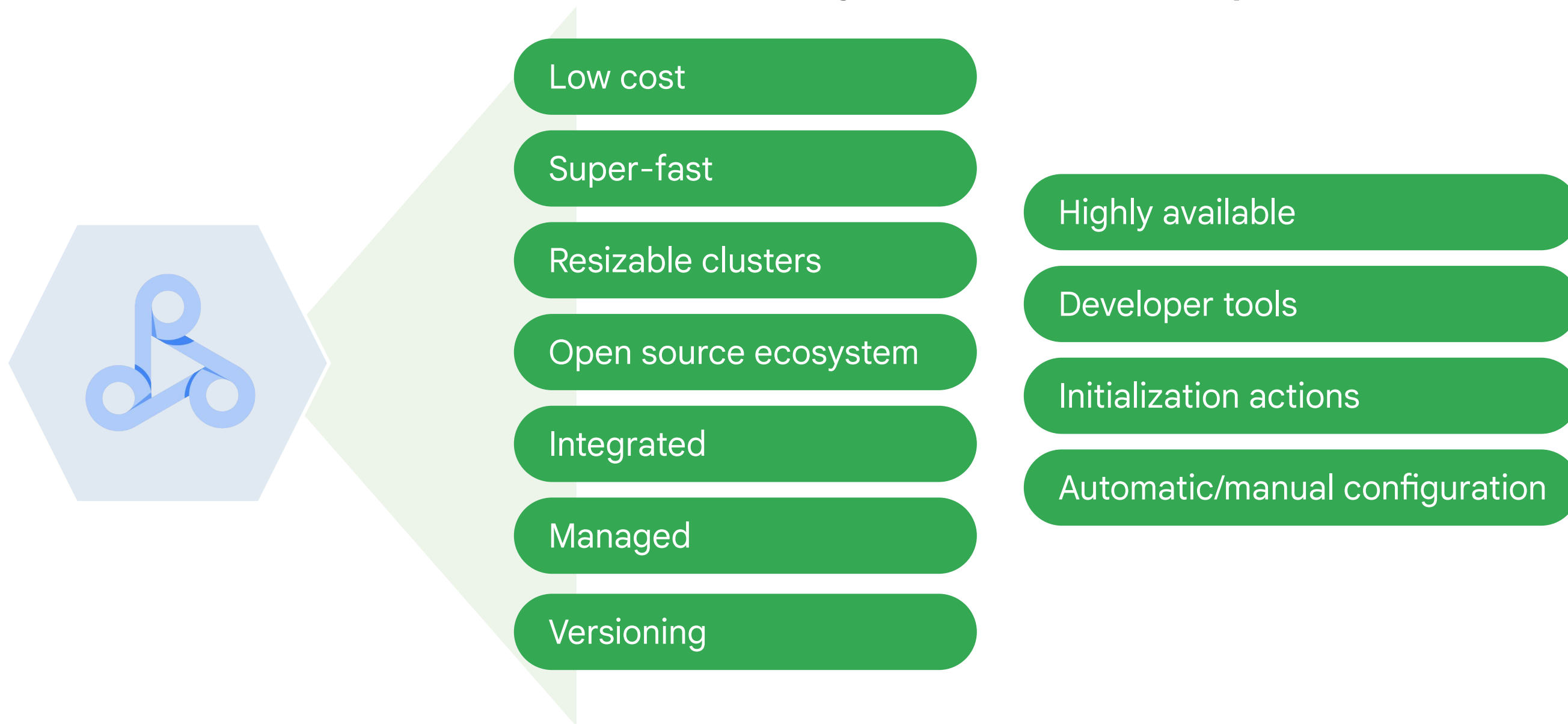
# Introduction to Building Batch Data Pipelines

01	The Hadoop ecosystem
02	Running Hadoop on Dataproc
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# Dataproc is a managed service for running Hadoop and Spark data processing workload

## Key features of Dataproc

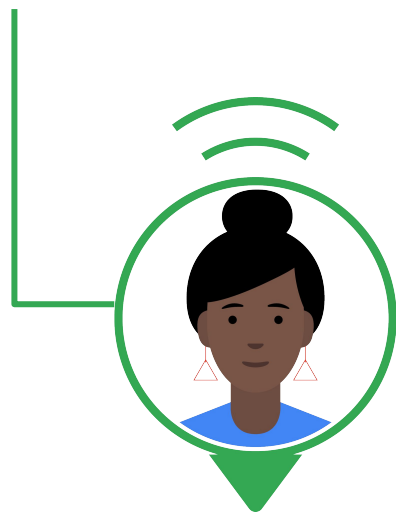


# There are other OSS options available in Dataproc

- Spark (default)
- Pig (default)
- Kafka
- Presto
- Jupyter
- IPython
- Much more...
- Hive (default)
- Zeppelin
- Hue
- Anaconda
- Apache Flink
- Oozie
- HDFS (default)
- Zookeeper
- Tez
- Cloud SQL Proxy
- Datalab
- Sqoop

# Use initialization actions to add other software to cluster at startup

Use **initialization actions** to install additional components on the cluster.

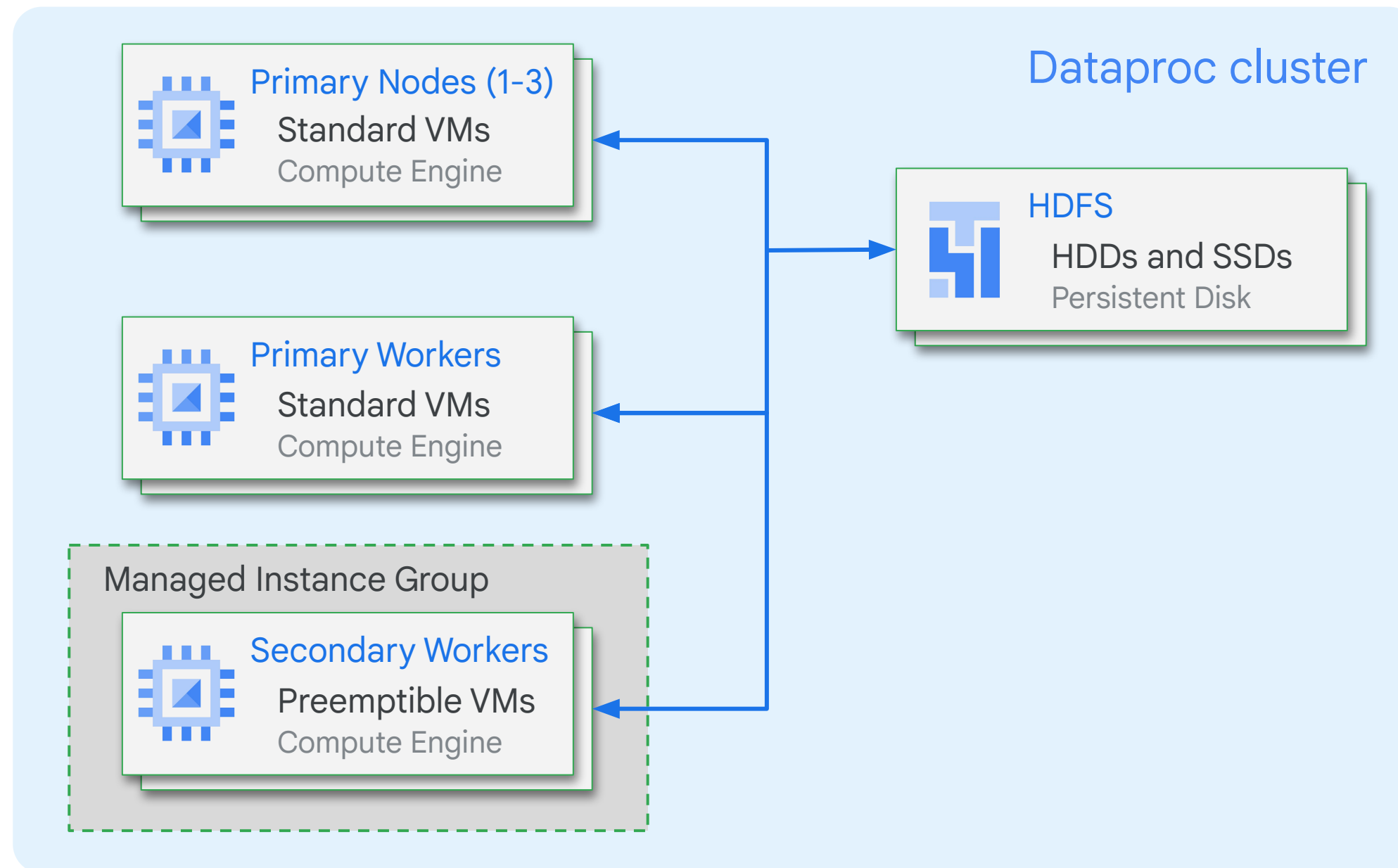


```
gcloud dataproc clusters create <CLUSTER_NAME> \
  --initialization-actions gs://$MY_BUCKET/hbase/hbase.sh \
  --num-masters 3 --num-workers 2
```

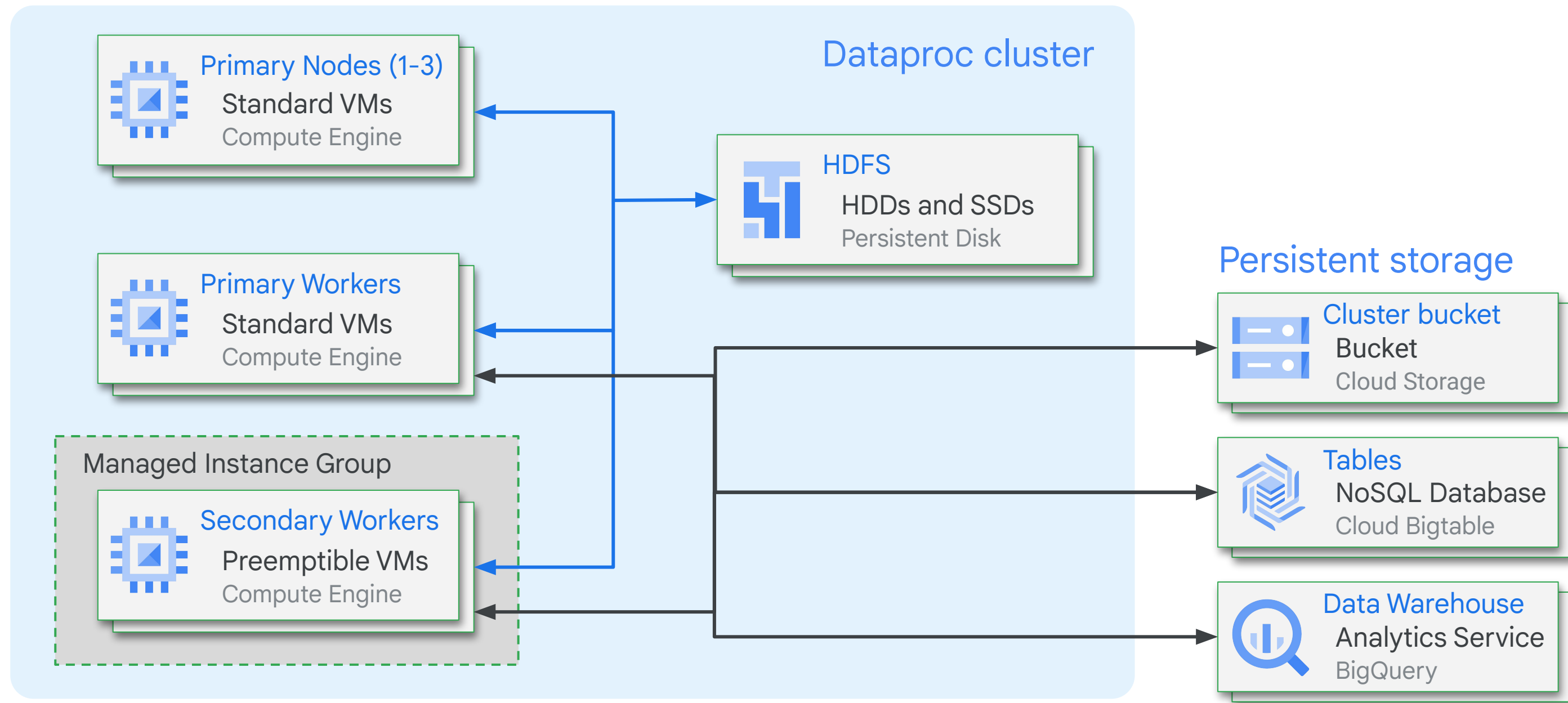
<https://github.com/GoogleCloudPlatform/dataproc-initialization-actions>

(Flink, Jupyter, Oozie, Presto, Tez, HBase, etc.)

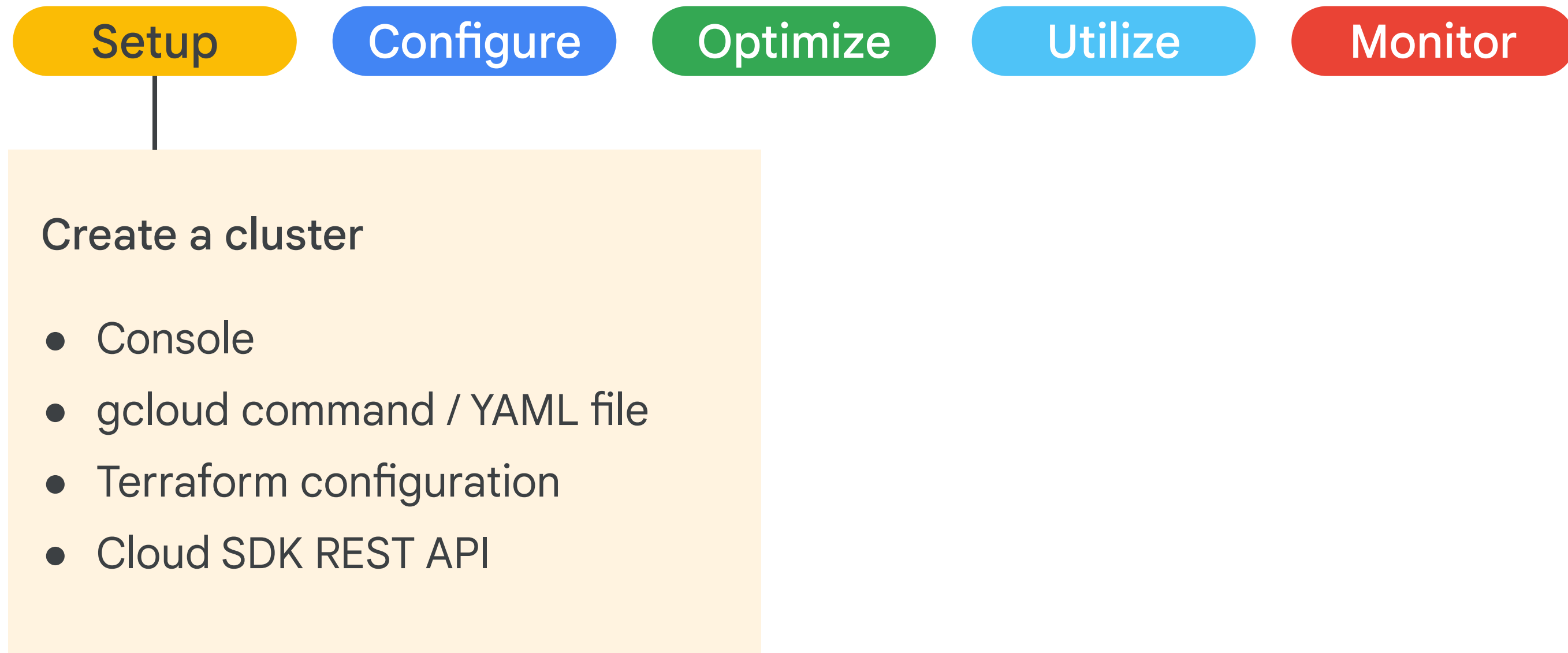
# A Dataproc cluster has primary nodes, workers, and HDFS



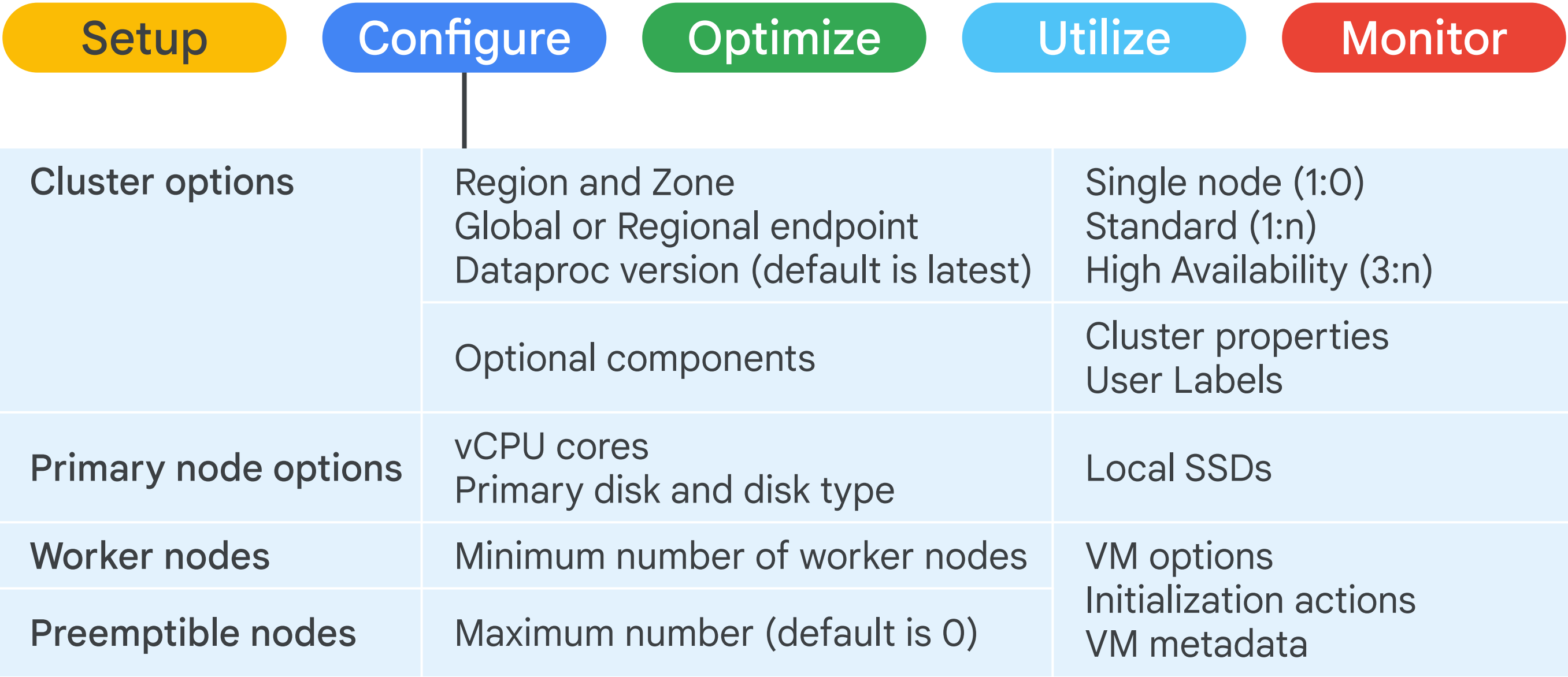
# Dataproc cluster can read/write to Google Cloud storage products



# Using Dataproc



# Configure





# Optimize

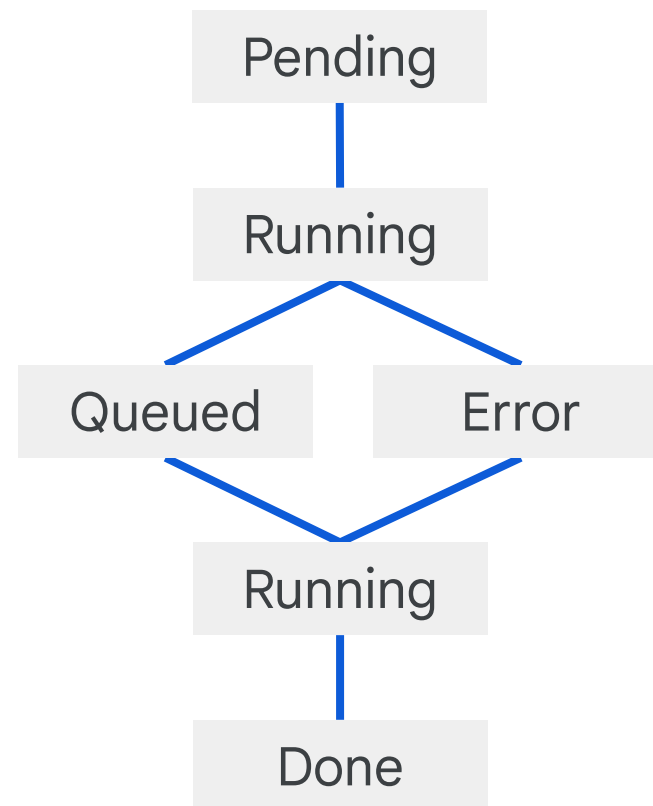


Preemptible VMs	Lower cost.
Custom machine types	Efficient allocation of resources for consistent workloads.
Minimum CPU platform	Consistent distribution of workload -minimum vCPU performance.
Custom images	Faster time to reach an operational state.
Persistent SSD boot disk	Faster boot time.
Attached GPUs	Faster processing for some workloads.
Dataprocs version	Specify to prevent changes, or default to the latest.

# Utilize: Job submission

**Setup****Configure****Optimize****Utilize****Monitor**

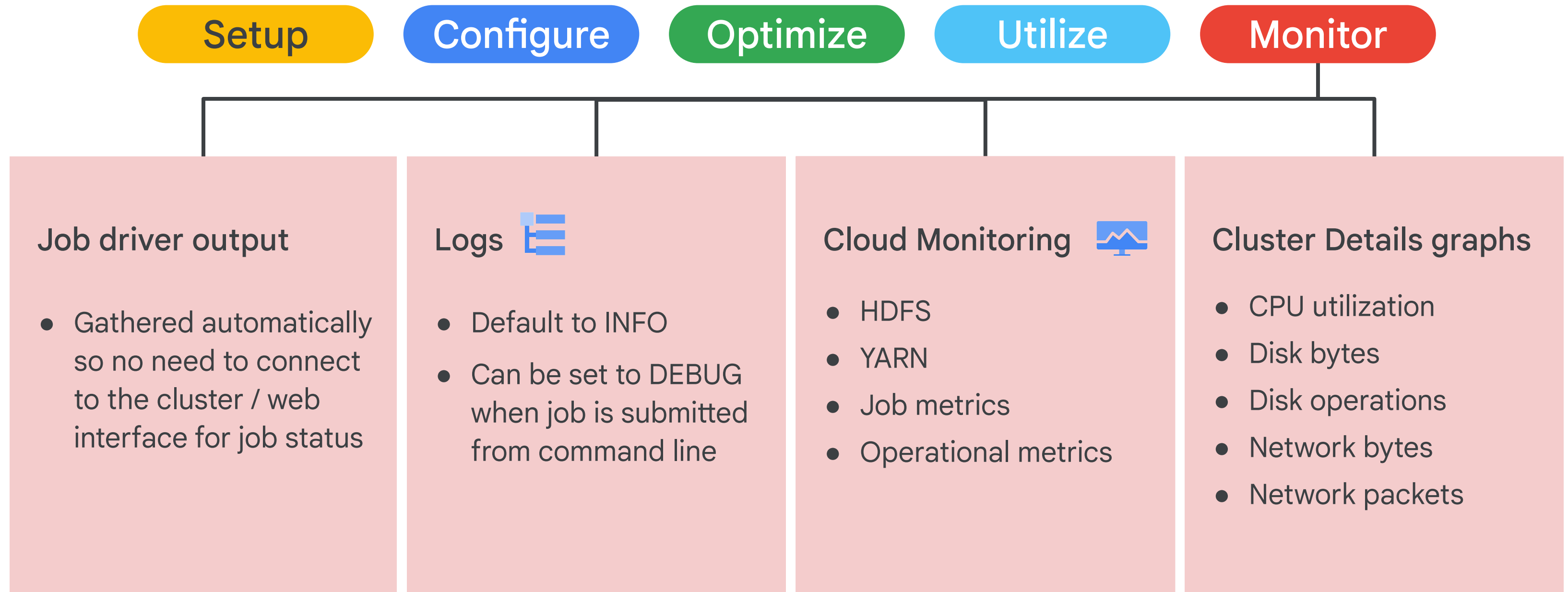
## Job Lifecycle



## Submit a job

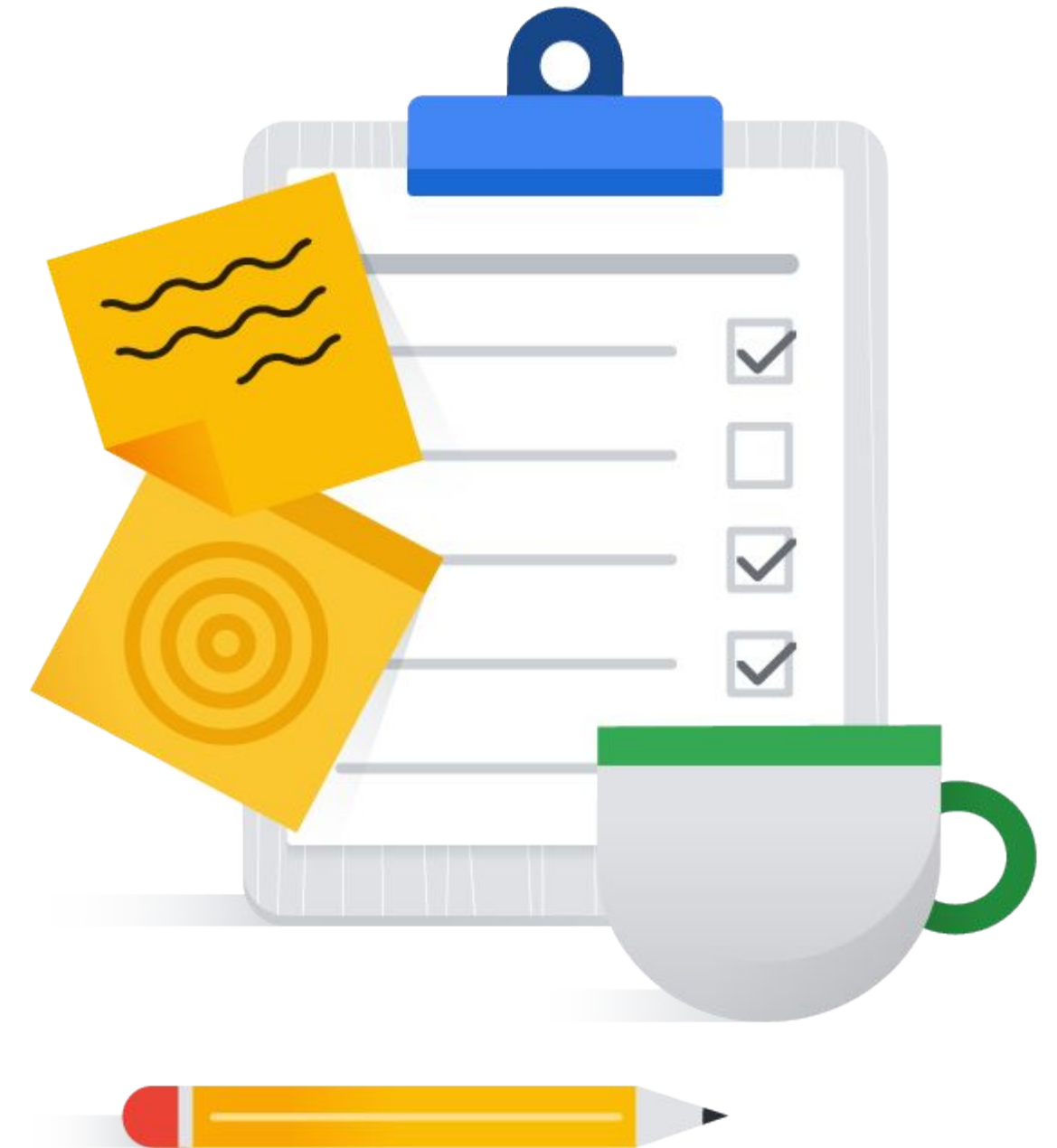
- Console
- gcloud command
- REST API
- Orchestration services:
  - Dataproc Workflow Templates
  - Cloud Composer

# Monitor through Console and Cloud Monitoring

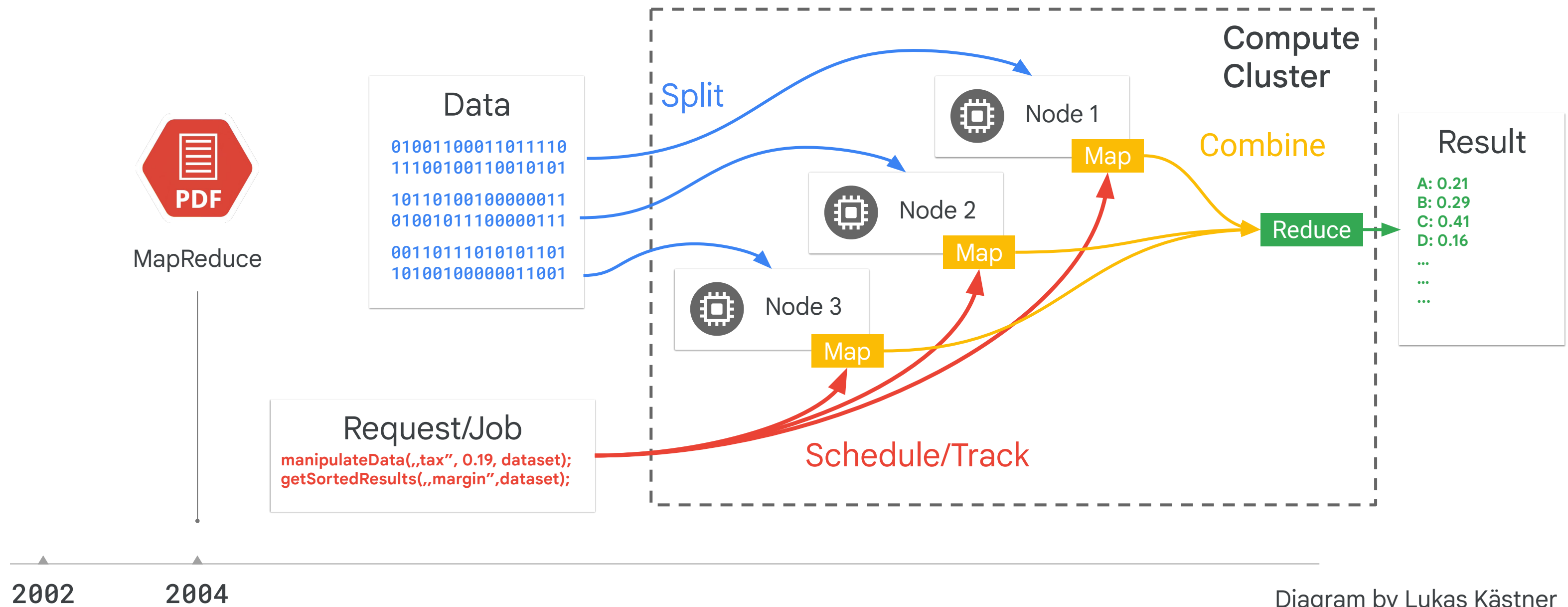


# Executing Spark on Dataproc

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# The original MapReduce paper was designed for a world where data was local to the compute machine



# HDFS in the Cloud is a sub-par solution

01

## Block size

Defaults to 64 MB (often raised to 128 MB)

Determines parallelism of execution

I/O scales with disk size & VM cores (up to 2 TB and 8 cores)

Only accessible from a single node (in RW mode)

Compute and storage are not independent, adding to costs

02

## Locality

HDFS spreads blocks

Most execution engines on HDFS are locality aware

If you use persistent disks, then data locality no longer holds

03

## Replication

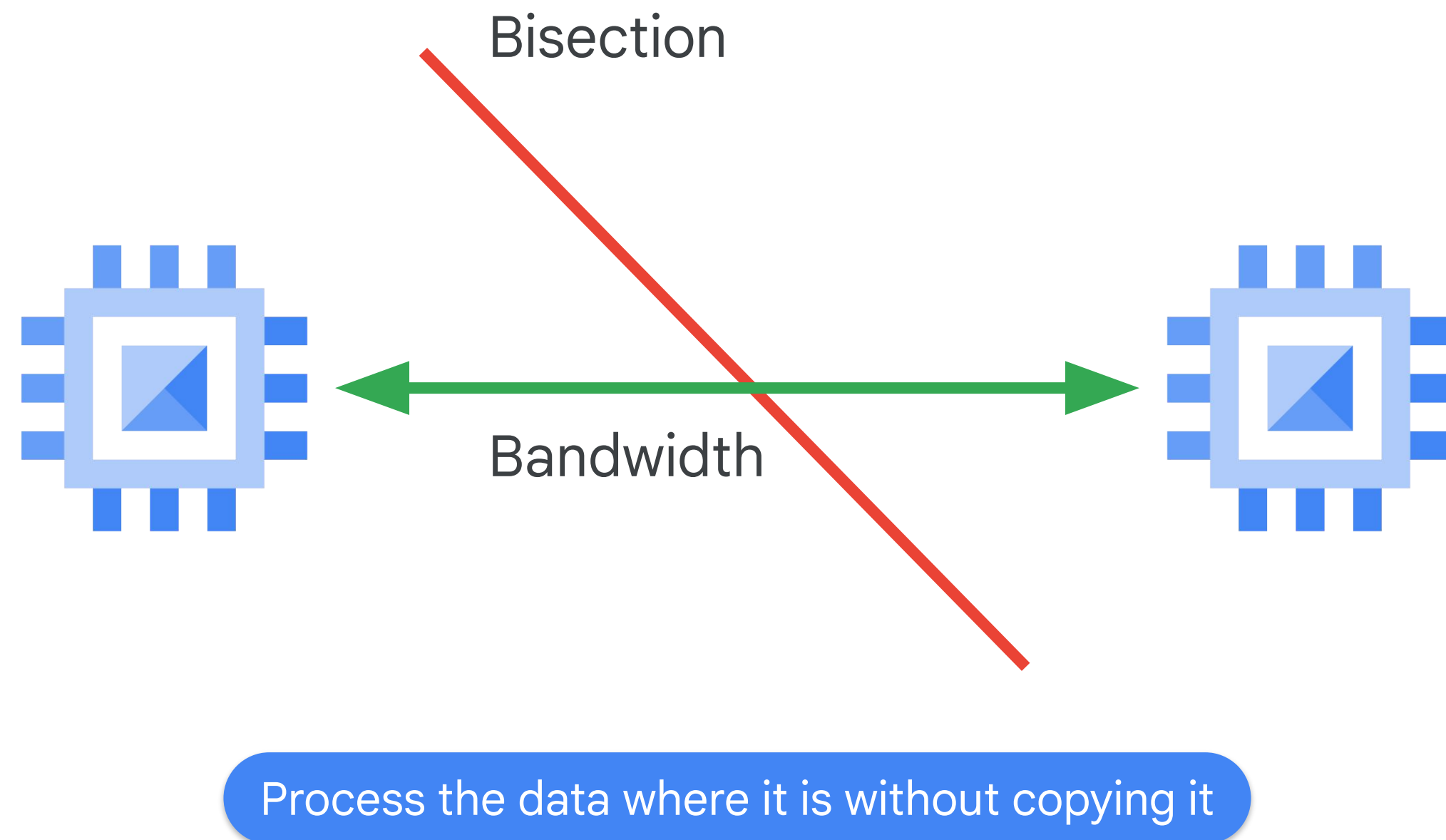
Default to 3 copies of each block ( $r=3$ )

Still need  $r = 2$  on HDFS, for availability

- Dataproc servers have to transmit  $2 \times 3 = 6$  copies of HDFS blocks to Colossus.

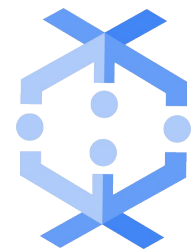
Lots of data replication makes this expensive

# Petabit bandwidth is a game-changer for big data



# On Google Cloud, Jupiter and Colossus make separation of compute and storage possible

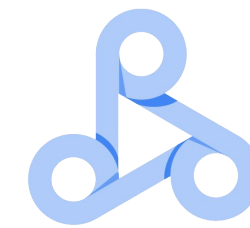
Processing



Dataflow



BigQuery  
Analytics



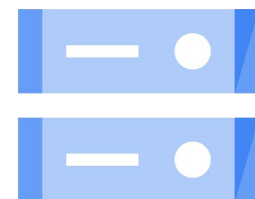
Dataproc

Start cluster  
Run job  
Delete cluster

Petabit bisection bandwidth

---

Storage



Cloud  
Storage  
(files)



BigQuery  
Storage  
(tables)

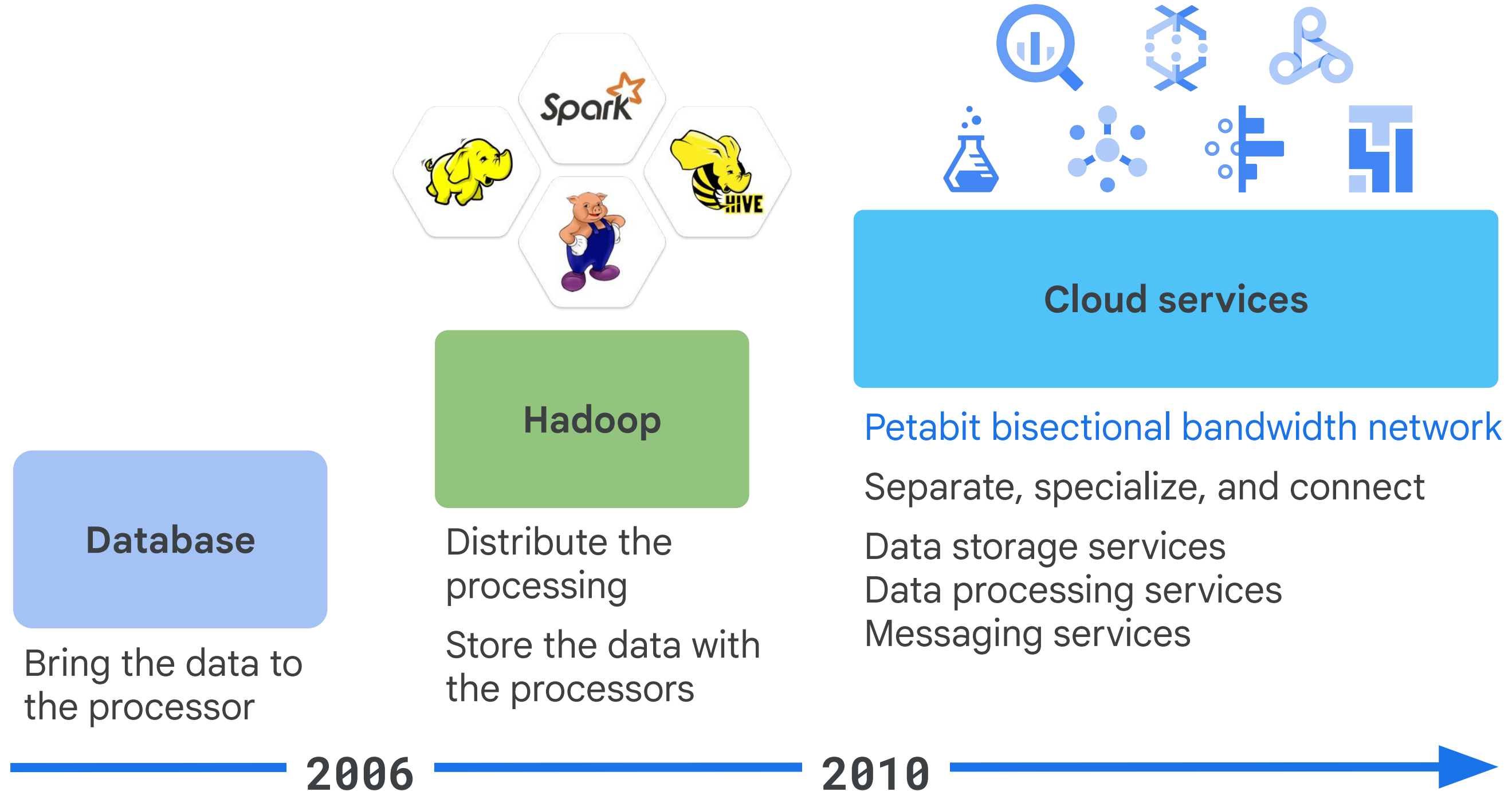


Cloud  
Bigtable  
(NoSQL)

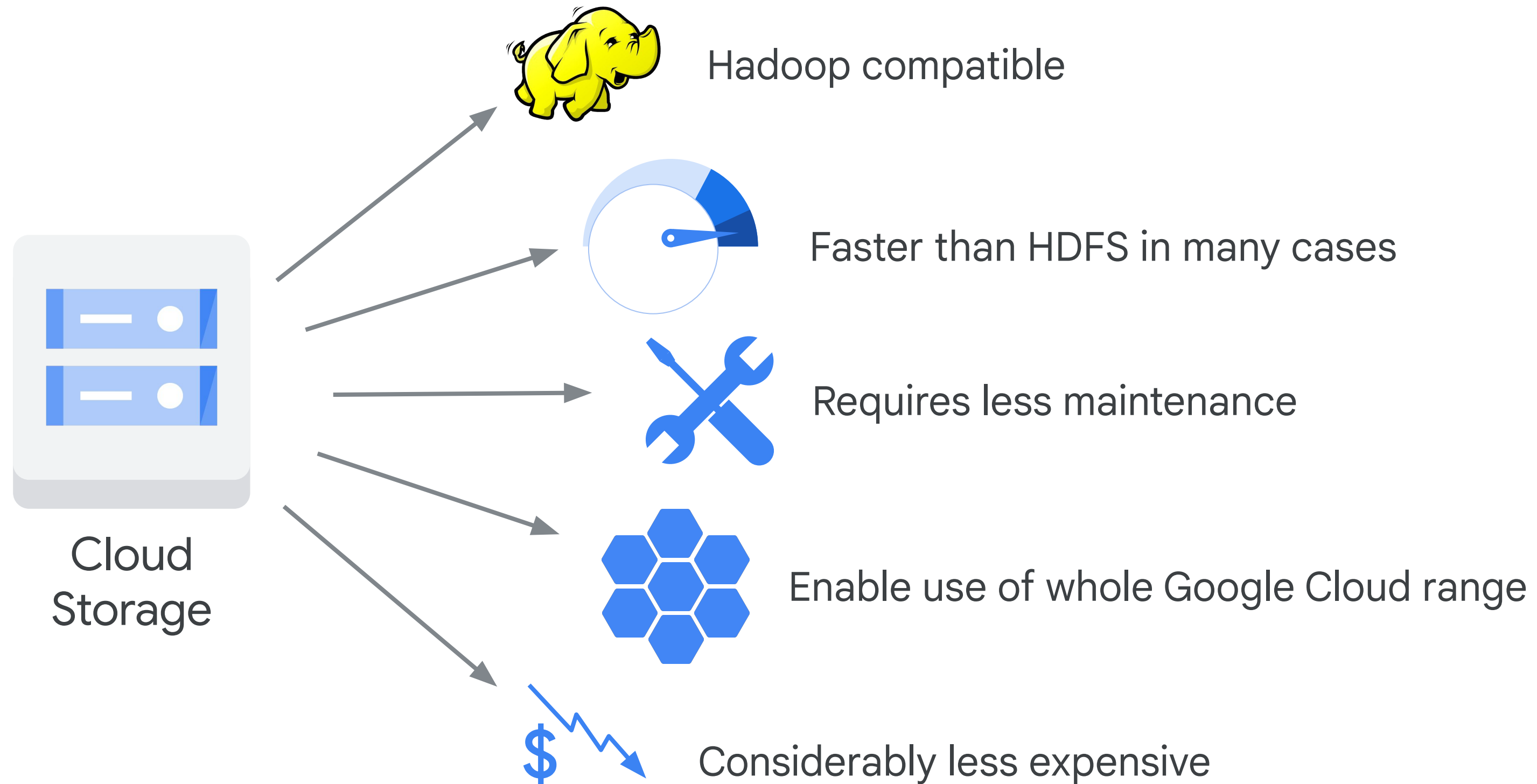
Keep data in  
place on Cloud  
Storage



# Separation of compute and storage enables better options



# Use Cloud Storage as the persistent data store



# Cloud Storage is a drop-in replacement for HDFS

- ✓ Hadoop FileSystem interfaces - "HCFS" compatible (Hadoop Compatible File System) File[Input|Output]Format, SparkContext.textFile, etc., just work
- ✓ Cloud Storage connector can be installed manually on non-Dataproc clusters

# Performance best practices

Cloud Storage is optimized for bulk/parallel operations

- ✓ Avoid small reads; use large block sizes where possible.
- ✓ Avoid iterating sequentially over many nested directories in a single job.

# Use Cloud Storage instead of HDFS with Dataproc

Setup

Configure

Optimize

Utilize

Monitor

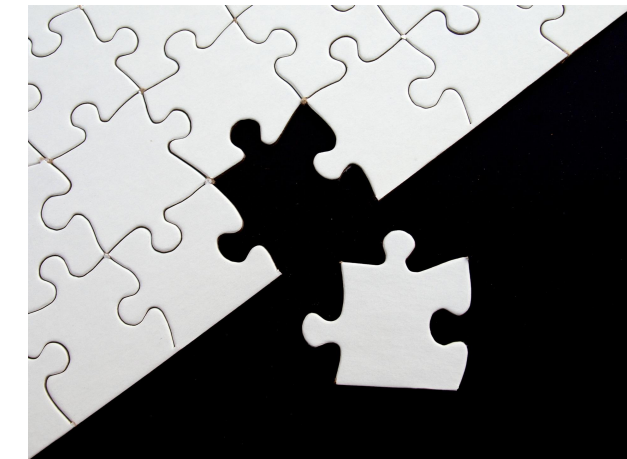


Cloud Storage is a distributed service

Eliminates traditional bottlenecks and single points of failure



Directories are simulated, so renaming a directory involves renaming all the objects\*



Objects do not support "append"

# Directory rename in HDFS not the same as in Cloud Storage

Cloud Storage has no concept of directories!

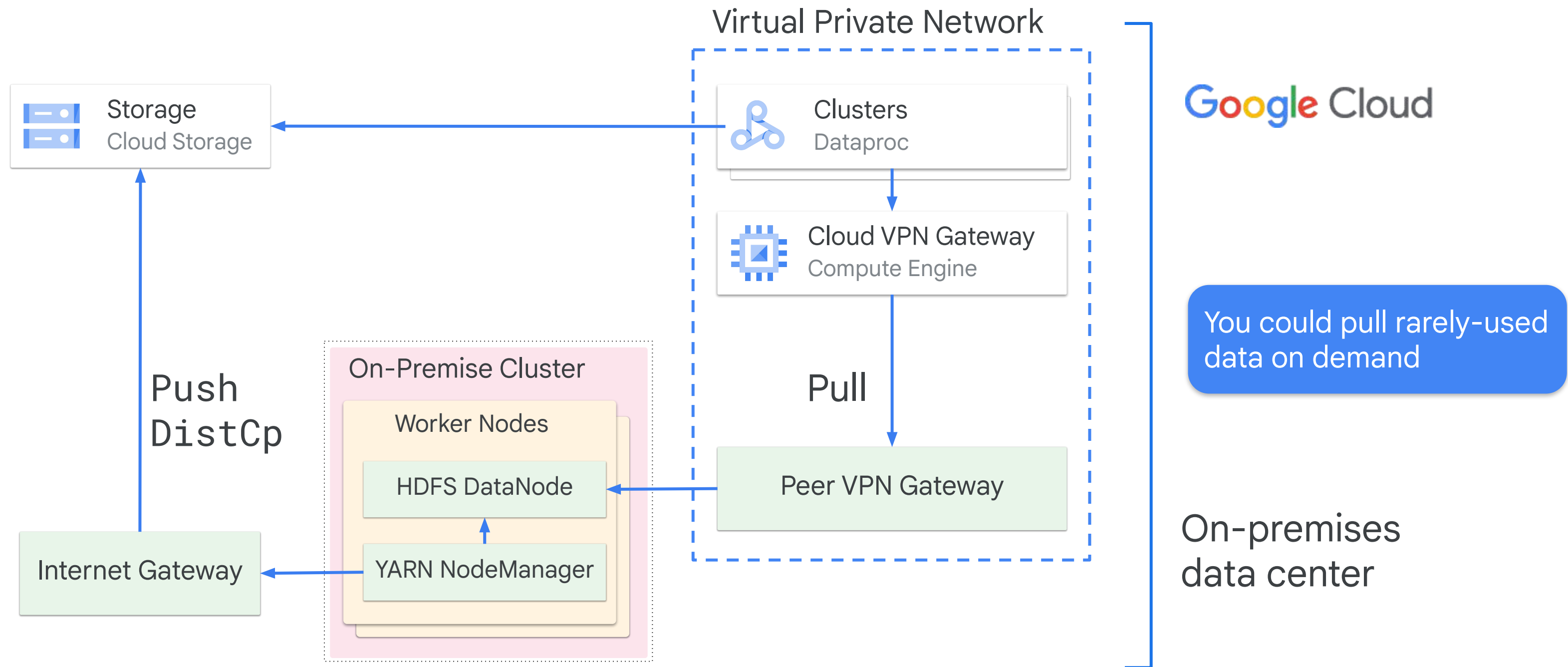
```
mv gs://foo/bar/ gs://foo/bar2
```

- `list(gs://foo/bar/)`
- `copy({gs://foo/bar/baz1, gs://foo/bar/baz2}, {gs://foo/bar2/baz1, gs://foo/bar2/baz2})`
- `delete({gs://foo/bar/baz1, gs://foo/bar/baz2})`

Migrated code should handle list inconsistency during rename!

- Modern output format committers handle object stores correctly

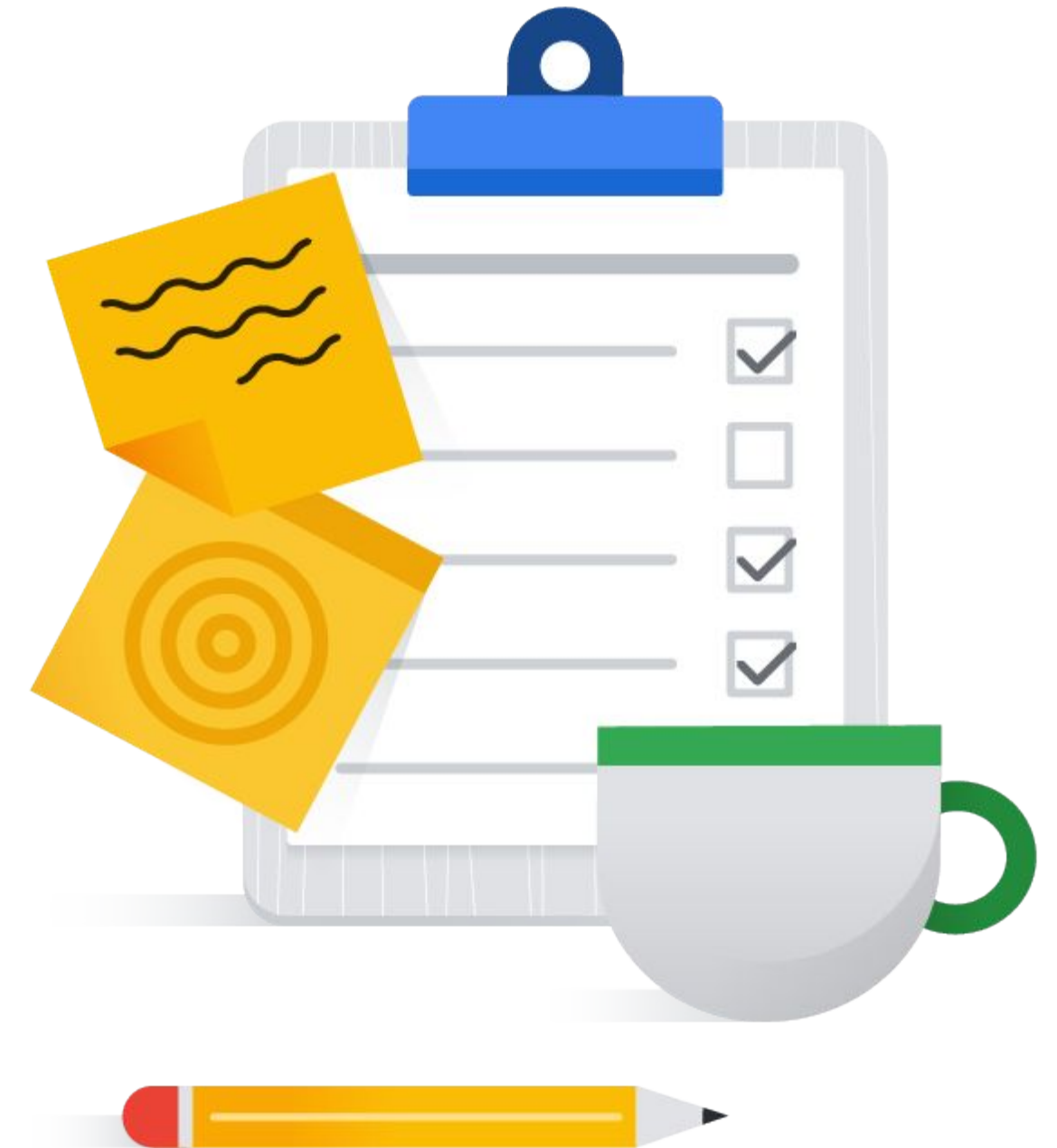
# DistCp on-prem data that you will always need



<https://hadoop.apache.org/docs/current/hadoop-distcp/DistCp.html>

# Executing Spark on Dataproc

01	The Hadoop ecosystem
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# Hadoop and Spark performance questions for all cluster architectures, Dataproc included

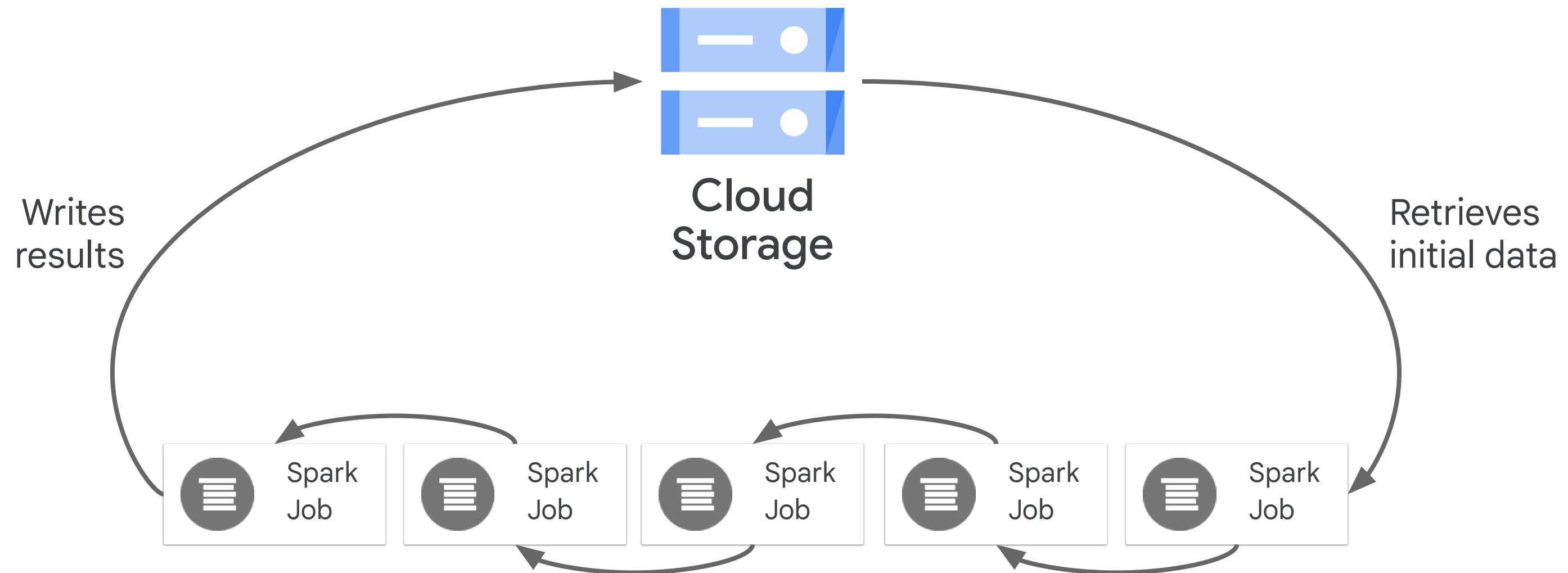
- 1 Where is your data, and where is your cluster?
- 2 Is your network traffic being funneled?
- 3 How many input files and Hadoop partitions are you trying to deal with?
- 4 Is the size of your persistent disk limiting your throughput?
- 5 Did you allocate enough virtual machines (VMs) to your cluster?

# Local HDFS is necessary at times

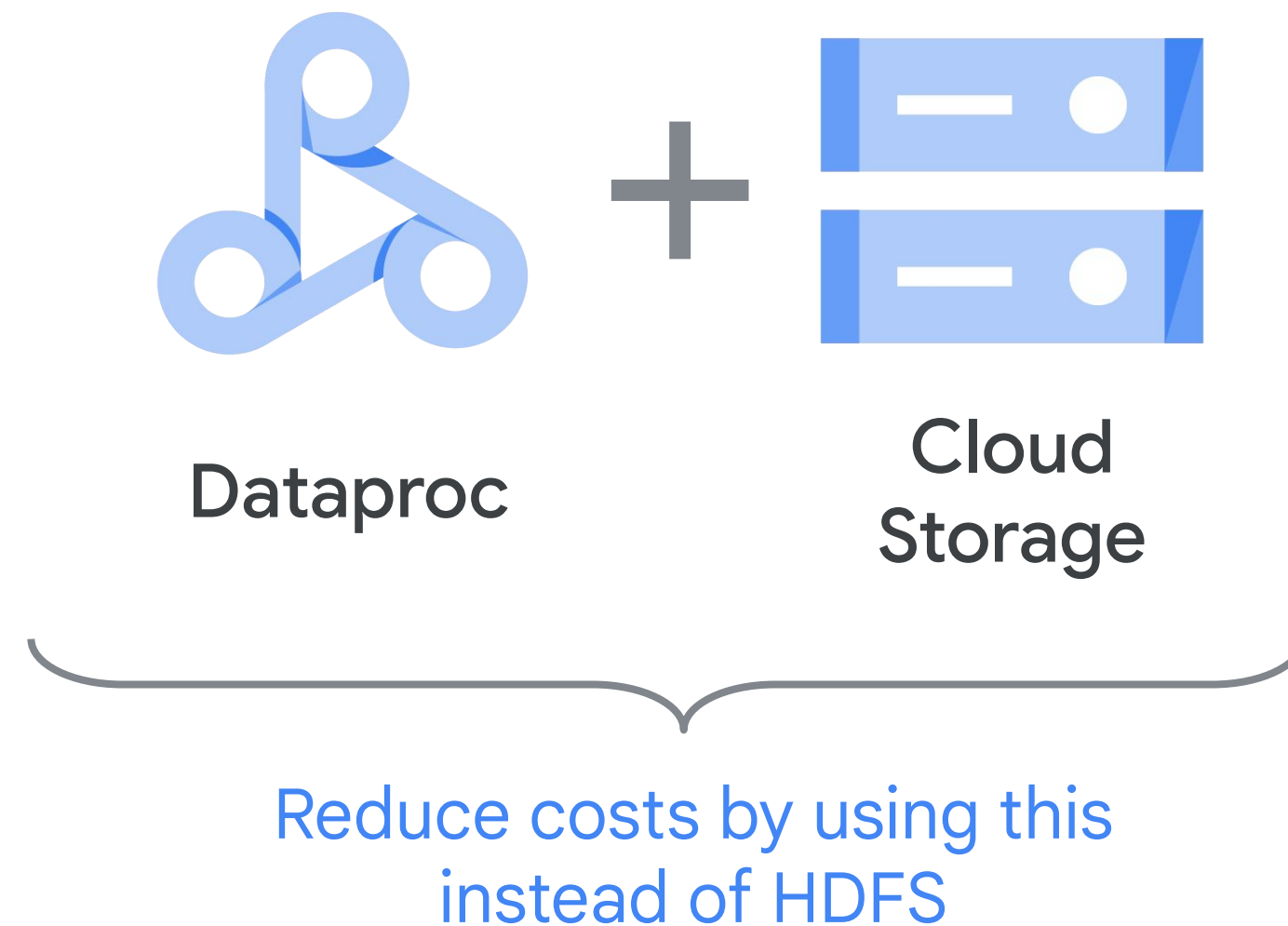
Local HDFS is a good option if:

- Your jobs require a lot of metadata operations.
- You modify the HDFS data frequently or you rename directories.
- You heavily use the append operation on HDFS files.
- You have workloads that involve heavy I/O -  
`spark.read().write.partitionBy(...).parquet("gs://")`
- You have I/O workloads that are especially sensitive to latency.

# Cloud Storage works well as the initial and final source of data in a big-data pipeline



# Using Dataproc with Cloud Storage allows you to reduce the disk requirements and save costs



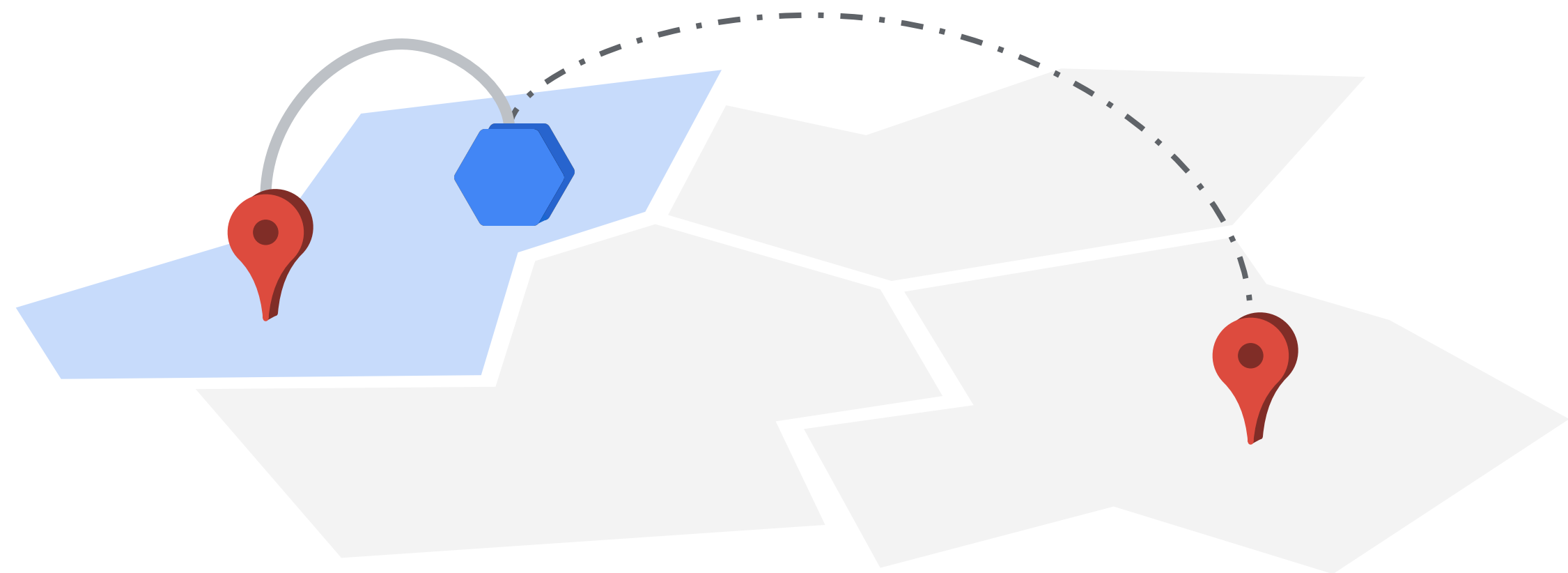
# Using local HDFS? Consider re-sizing options

- Decrease the total size of the local HDFS by decreasing the size of primary persistent disks for the primary and workers.
- Increase the total size of the local HDFS by increasing the size of primary persistent disk for workers.
- Attach up to eight SSDs (375 GB each) to each worker and use these disks for the HDFS.
- Use SSD persistent disks for your primary or workers as a primary disk.

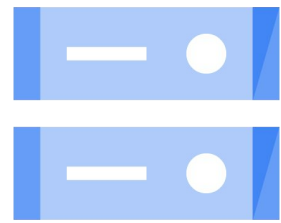
# Geographical regions can impact the efficiency of your solution

Regions can have repercussions for your jobs, such as:

- Request latency
- Data proliferation
- Performance



# Google Cloud provides different storage options for different jobs



## Cloud Storage

- Primary datastore for Google Cloud
- Unstructured data



## Cloud Bigtable

- Large amounts of sparse data
- HBase-compliant
- Low latency
- High scalability



## BigQuery

- Data warehousing
- Storage API makes this faster than before
- Could push down queries to BigQuery, refactoring the job

# Replicating your persistent on-premises setup has some drawbacks

01

Persistent clusters are expensive.

02

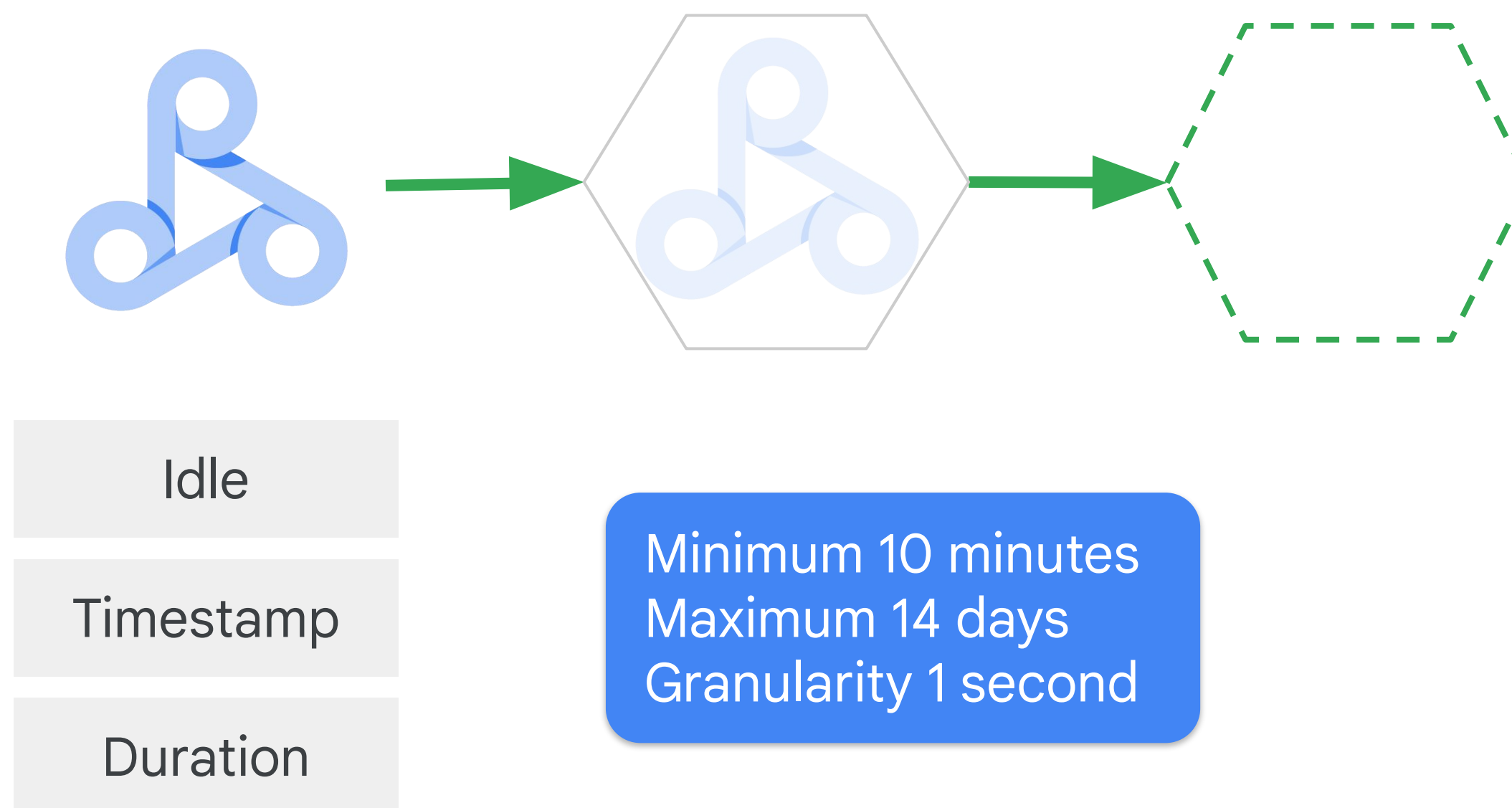
Your open-source-based tools may be inefficient.

03

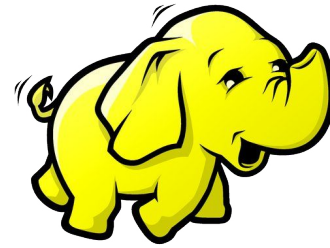
Persistent clusters are difficult to manage.



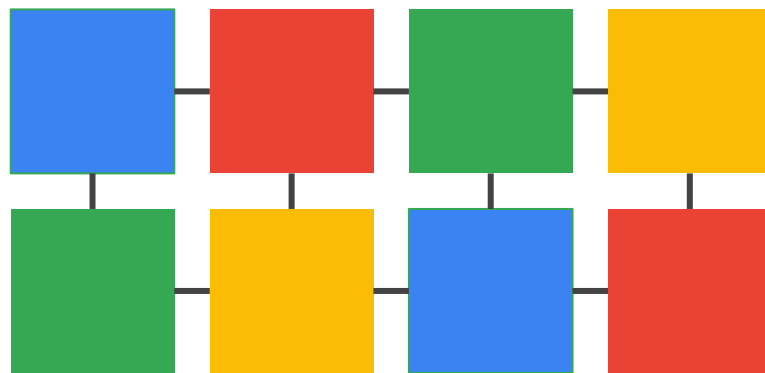
# Cluster Scheduled Deletion



# With ephemeral clusters, you only pay for what you use



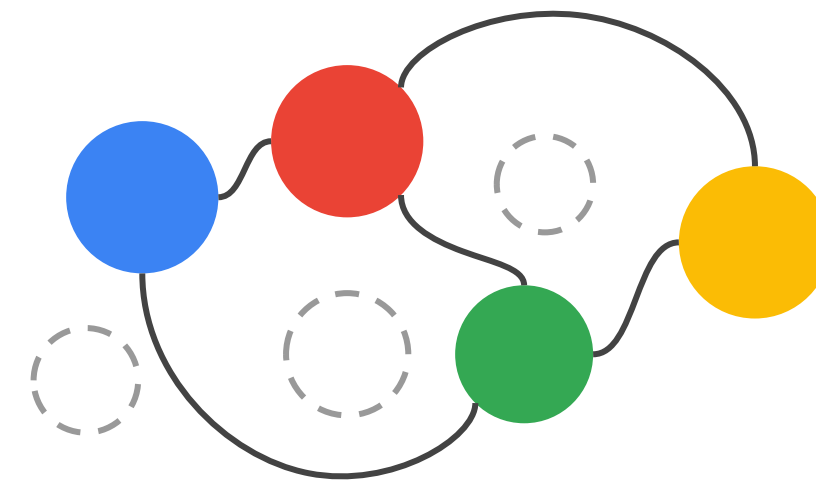
Persistent clusters



Resources are active at all times. You are constantly paying for all available clusters.

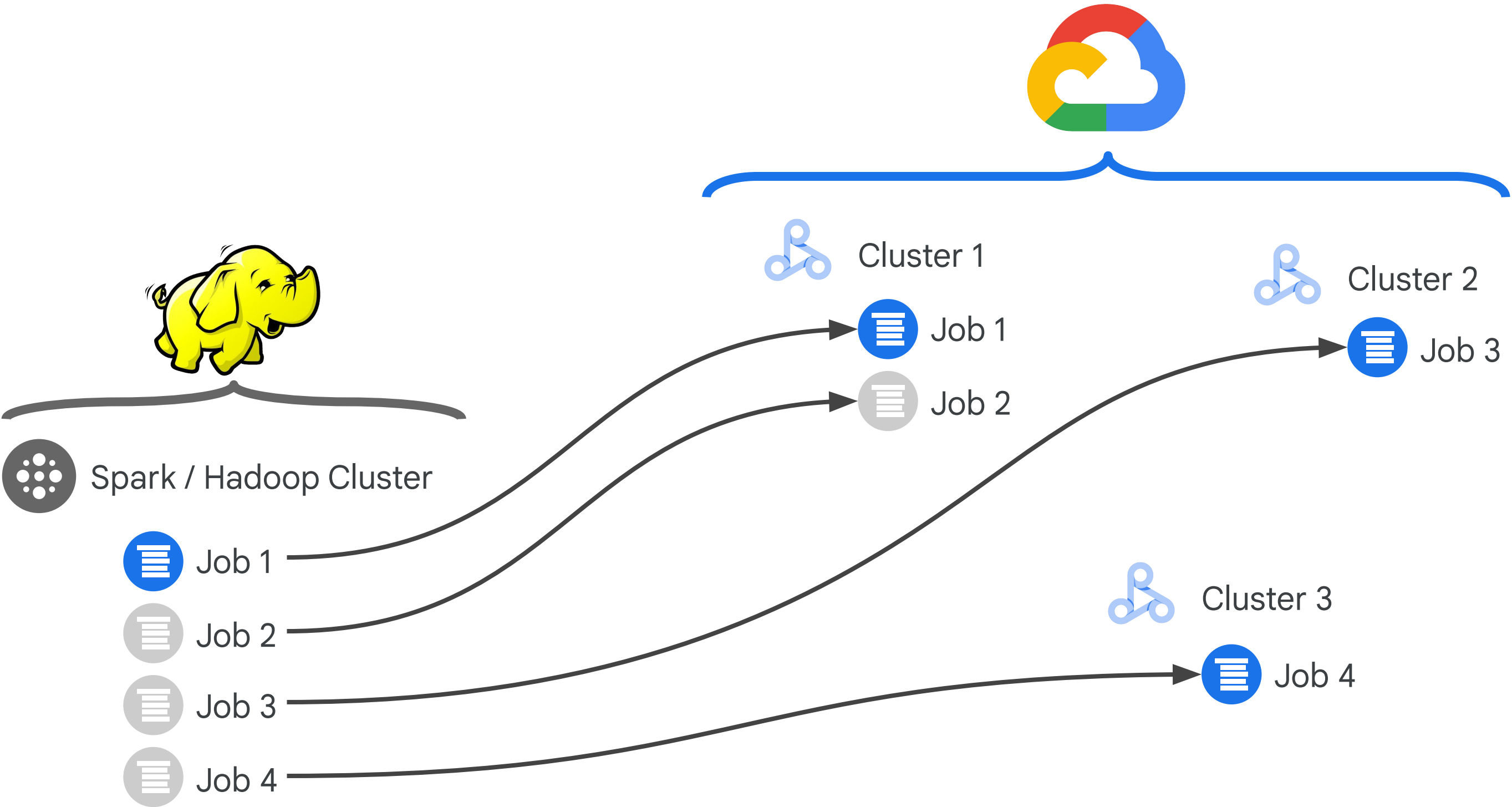


Ephemeral clusters



Required resources are active only when being used. You only pay for what you use.

# Split clusters and jobs



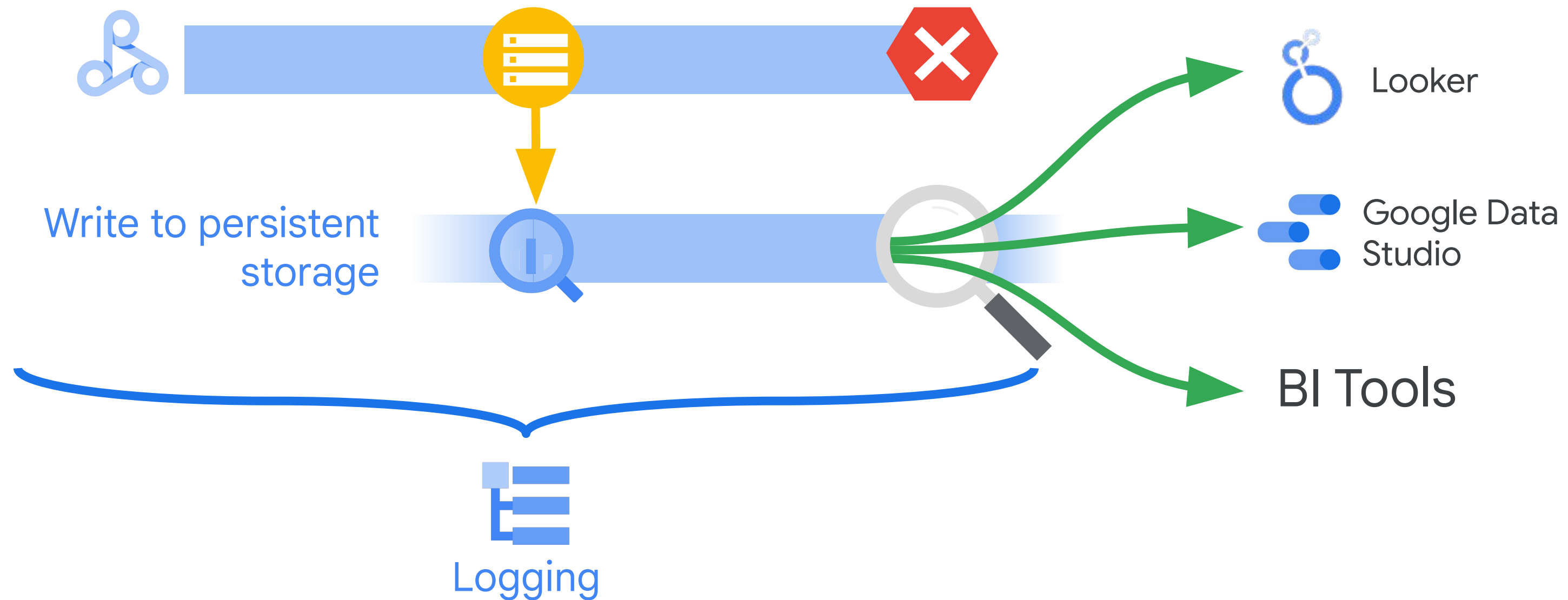
# Use ephemeral clusters for one job's lifetime

Create cluster

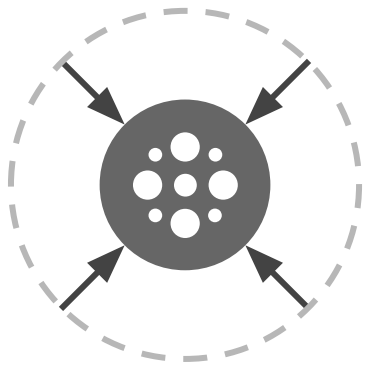
Run job

Delete cluster

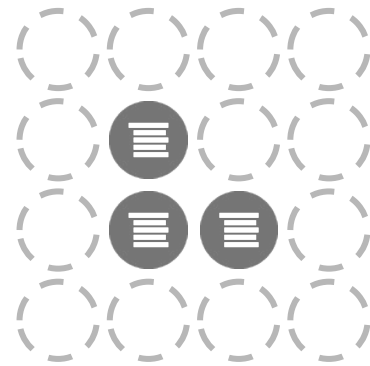
View output



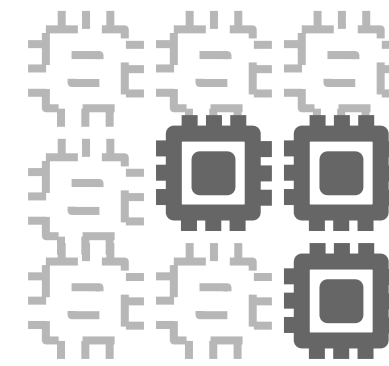
# Points to remember if you need a persistent cluster



**Create** the smallest cluster you can, using [preemptible VMs](#) based on time budget.

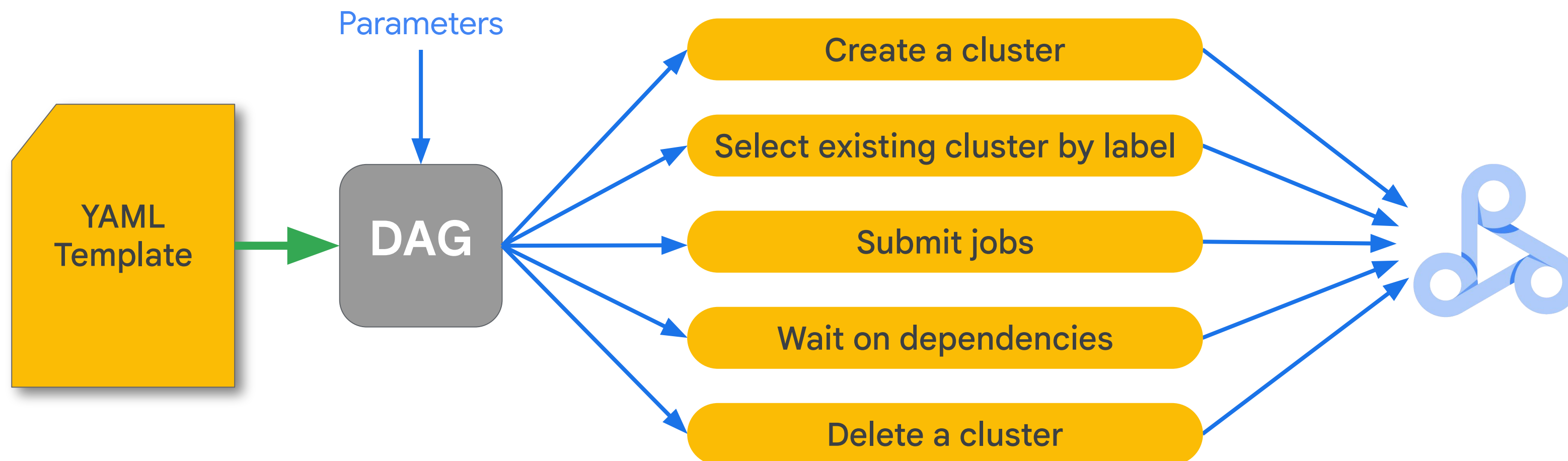


**Scope** your work on a persistent cluster to the smallest possible number of jobs.



**Scale** the cluster to the minimum workable number of nodes. Add more dynamically on demand ([auto-scaling](#)).

# Dataproc Workflow Template



# Dataproc workflow templates

```
# the things we need pip-installed on the cluster
STARTUP_SCRIPT=gs://{BUCKET}/sparktobq/startup_script.sh
echo "pip install --upgrade --quiet google-compute-engine google-cloud-storage matplotlib" >
/tmp/startup_script.sh
gsutil cp /tmp/startup_script.sh $STARTUP_SCRIPT

# create new cluster for job
gcloud dataproc workflow-templates set-managed-cluster $TEMPLATE \
  --master-machine-type $MACHINE_TYPE \
  --worker-machine-type $MACHINE_TYPE \
  --initialization-actions $STARTUP_SCRIPT \
  --num-workers 2 \
  --image-version 1.4 \
  --cluster-name $CLUSTER

# steps in job
gcloud dataproc workflow-templates add-job \
  pyspark gs://{BUCKET}/spark_analysis.py \
  --step-id create-report \
  --workflow-template $TEMPLATE \
  -- --bucket=$BUCKET

# submit workflow template
gcloud dataproc workflow-templates instantiate $TEMPLATE
```

# Dataproc workflow templates

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# submit workflow template
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# Dataproc workflow templates

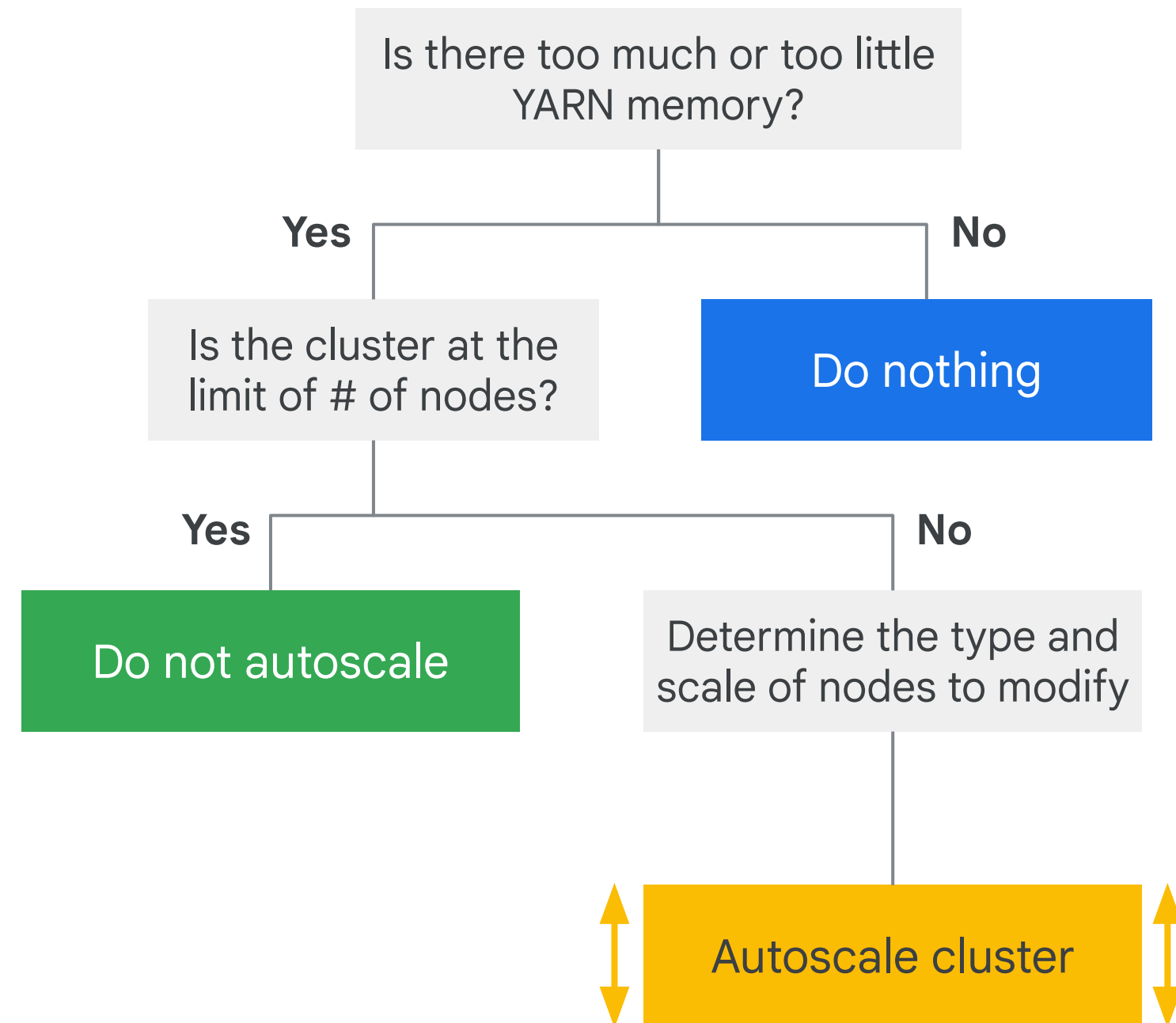
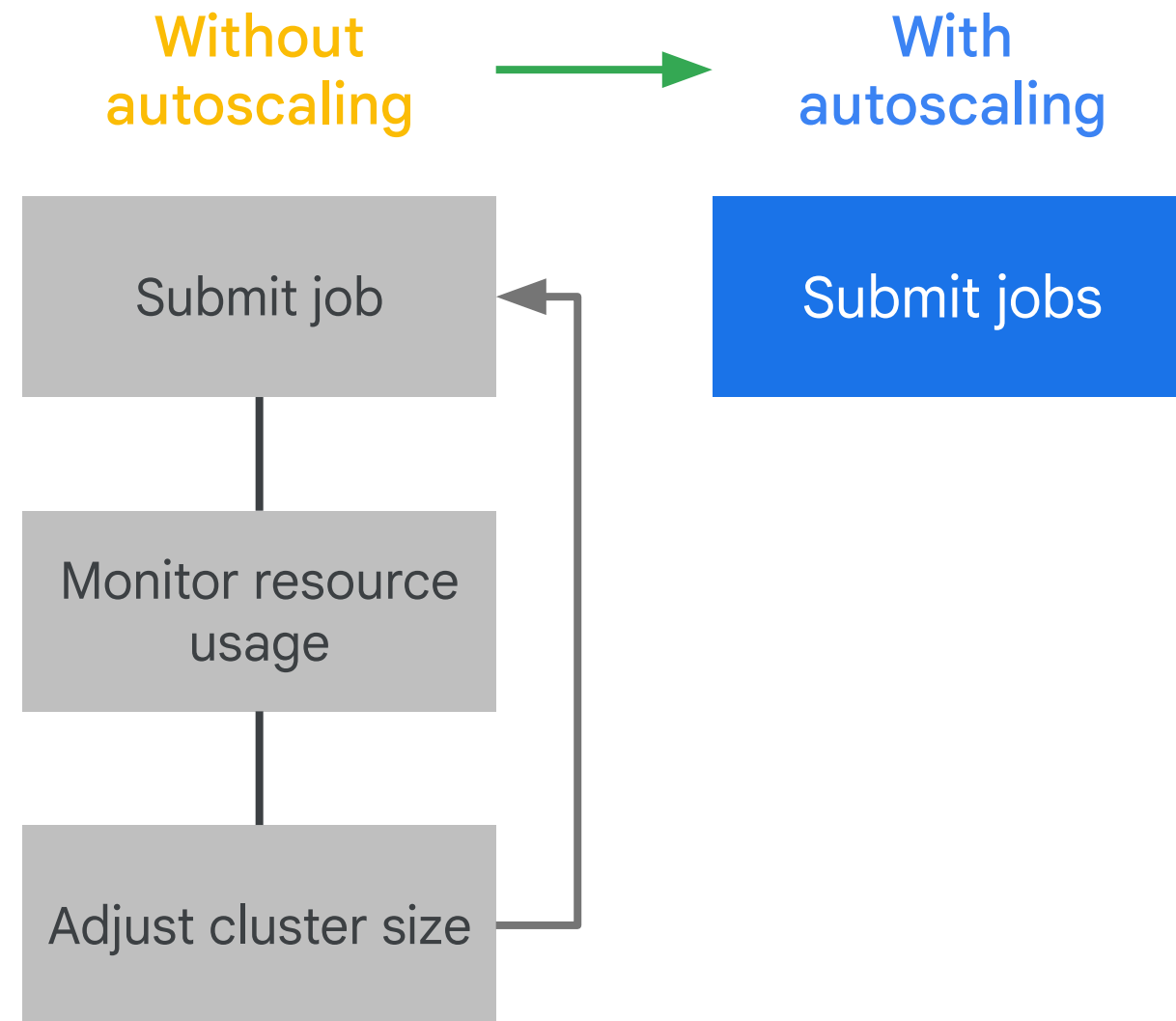
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# submit workflow template
gcloud dataproc workflow-templates instantiate $TEMPLATE
```

# Dataproc autoscaling workflow



# Autoscaling improvements

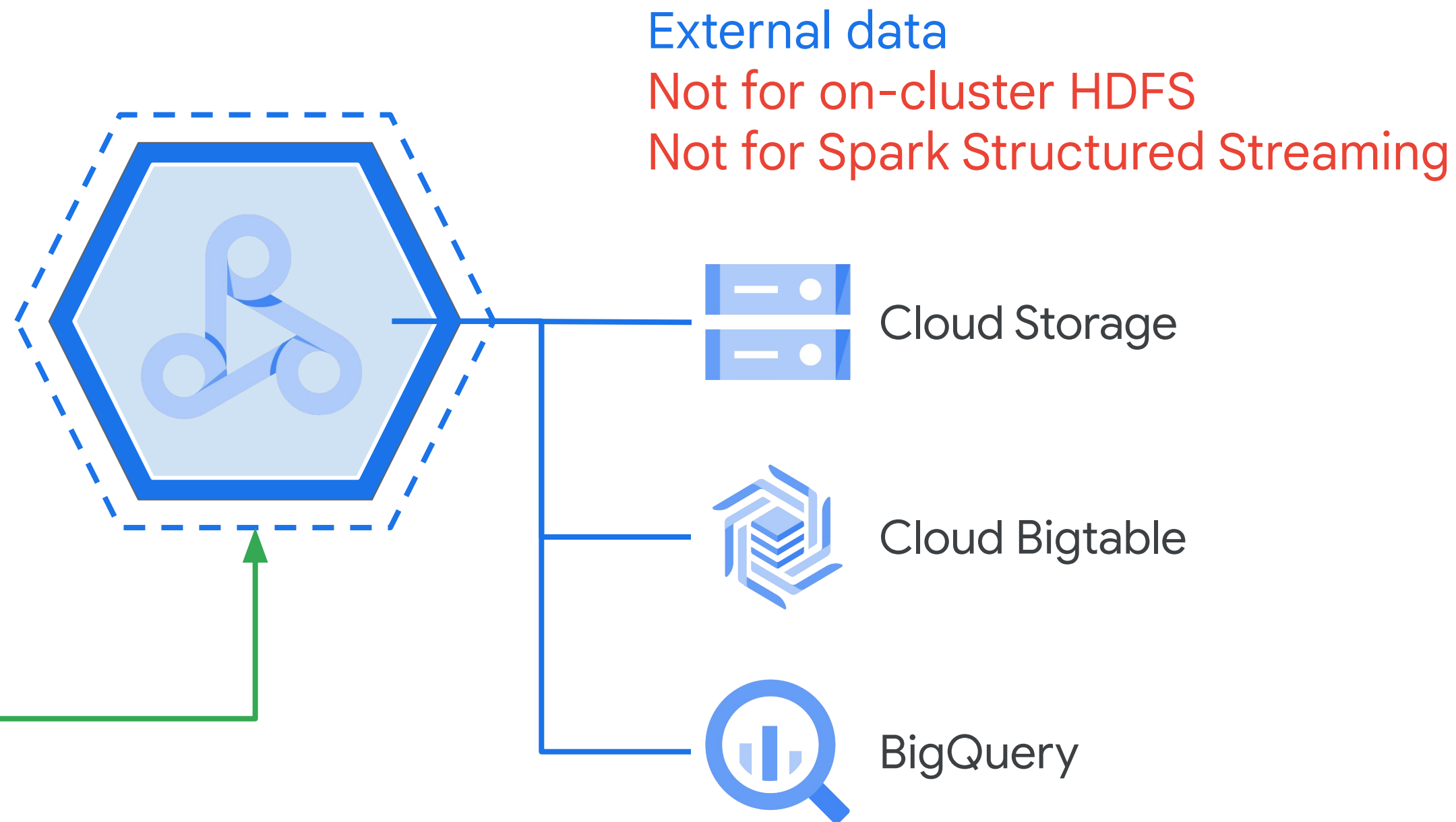
- ✓ Even more fine-grained controls
- ✓ Easier to understand
- ✓ Job stability

# Dataproc autoscaling provides flexible capacity

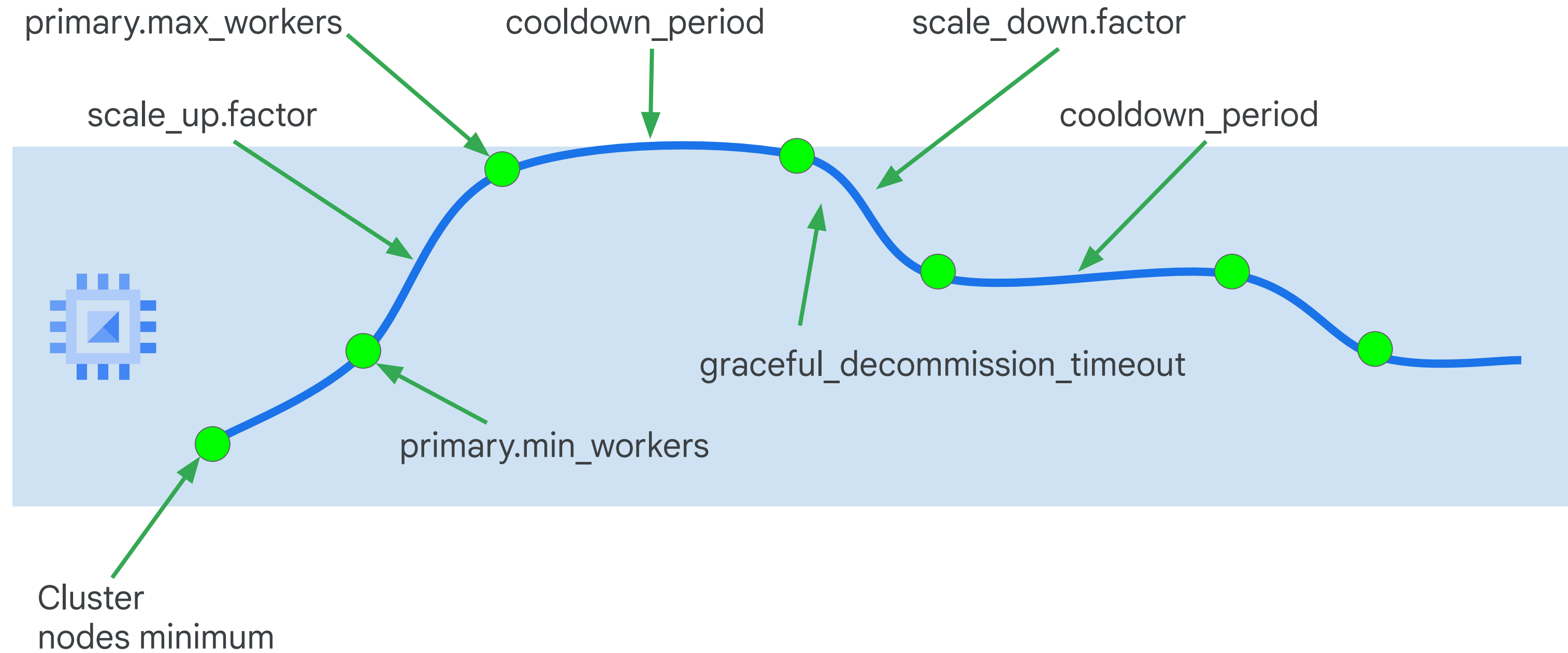
Cluster with lots of jobs  
or a single large job

Not for idle clusters or  
scale to zero

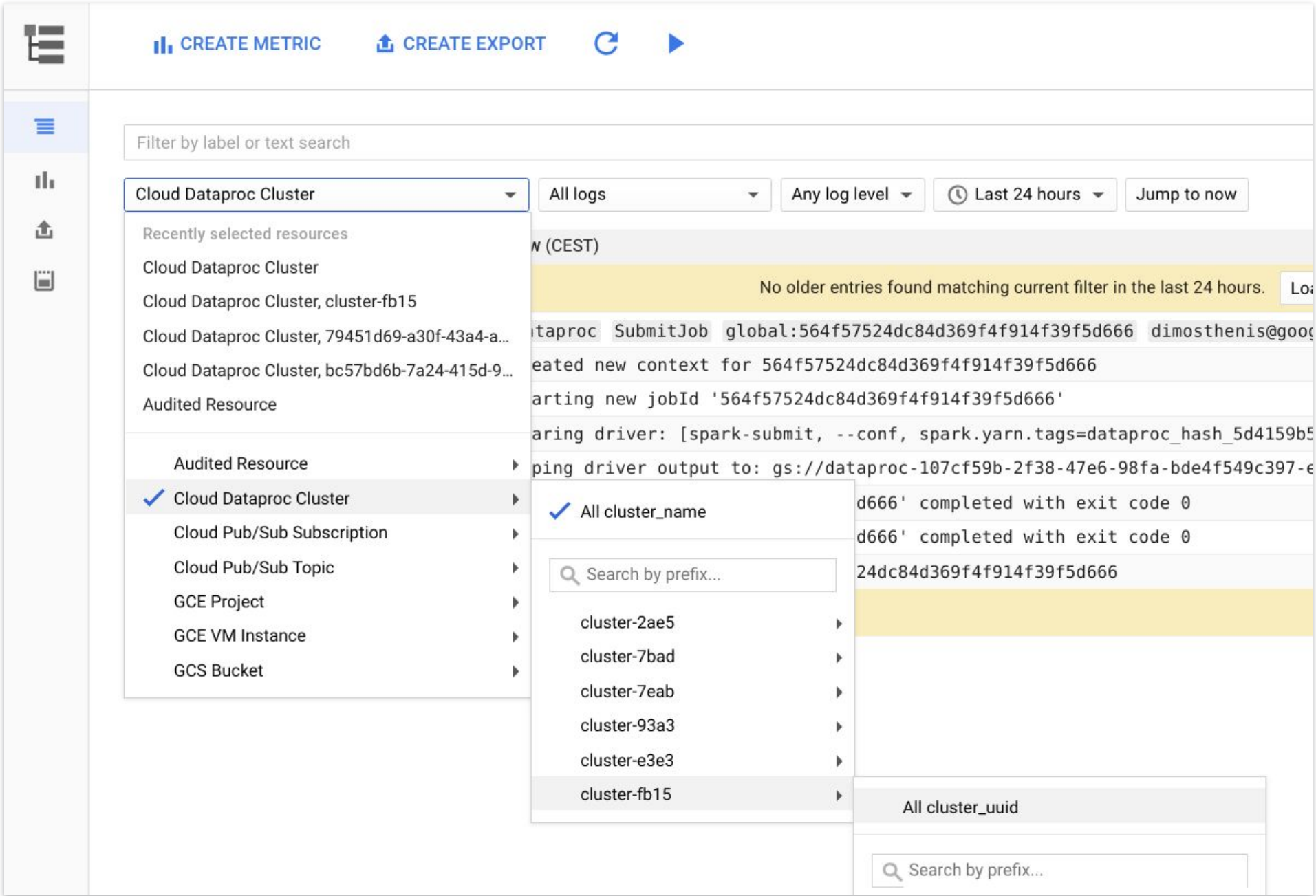
Autoscaling is based on  
Hadoop YARN Metrics



# How Dataproc autoscaling works

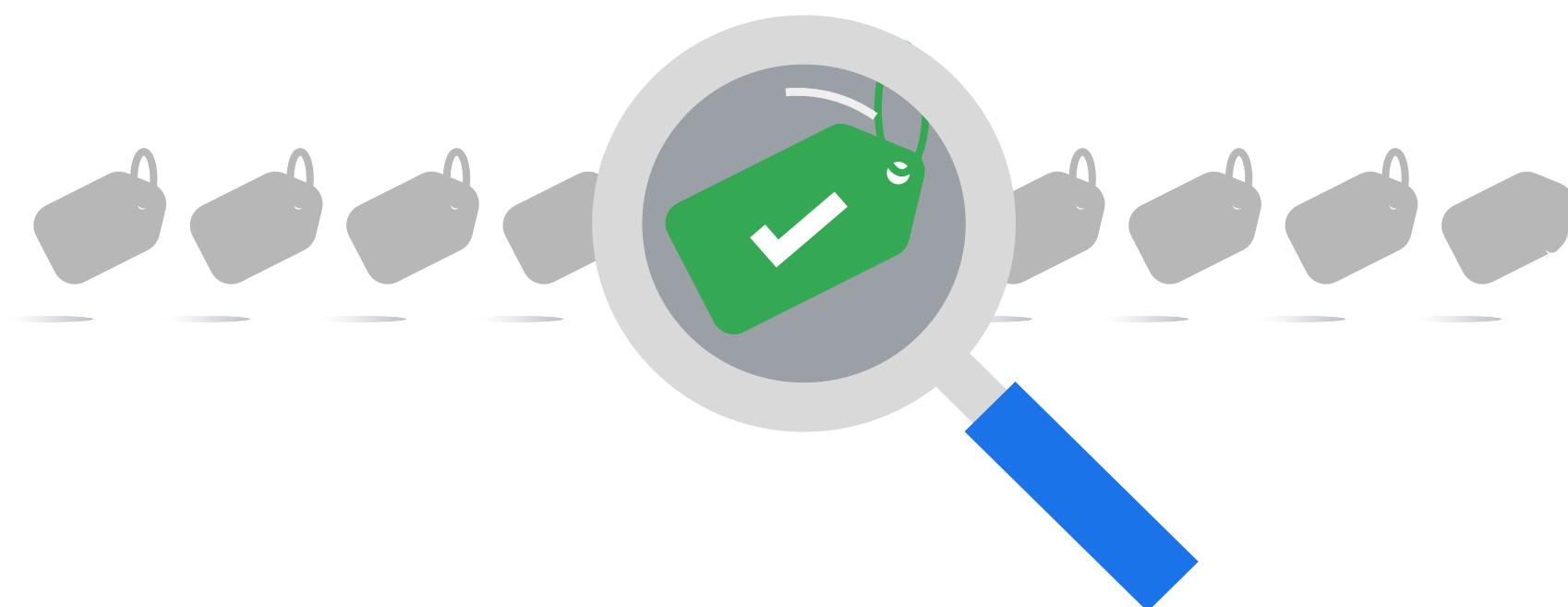


# Use Cloud Operations logging and performance monitoring





# Create labels on clusters and jobs to find logs faster



Filter by label or text search

Cloud Dataproc Job ▼ dataproc.job.driver

Showing logs from all time (PDT)

▼ \* 2019-04-03 09:34:16.478 PDT Pi is roughly 3.1417569

```
{
  insertId: "1e8i240nizp188ay9"
  labels: {...}
  logName: "projects/google.com:hadoop-cloud-dev/logs"
  receiveTimestamp: "2019-04-03T16:34:19.778423350Z"
  resource: {...}
  textPayload: "Pi is roughly 3.1417569514175696"
  timestamp: "2019-04-03T16:34:16.478380936Z"
}
```

▶ ⓘ 2019-04-03 09:34:16.000 PDT Stopped Spark@19569ebd{

▶ ⓘ 2019-04-03 09:33:45.000 PDT Submitted application a

# Set the log level

You can set the driver log level using the following gcloud command:

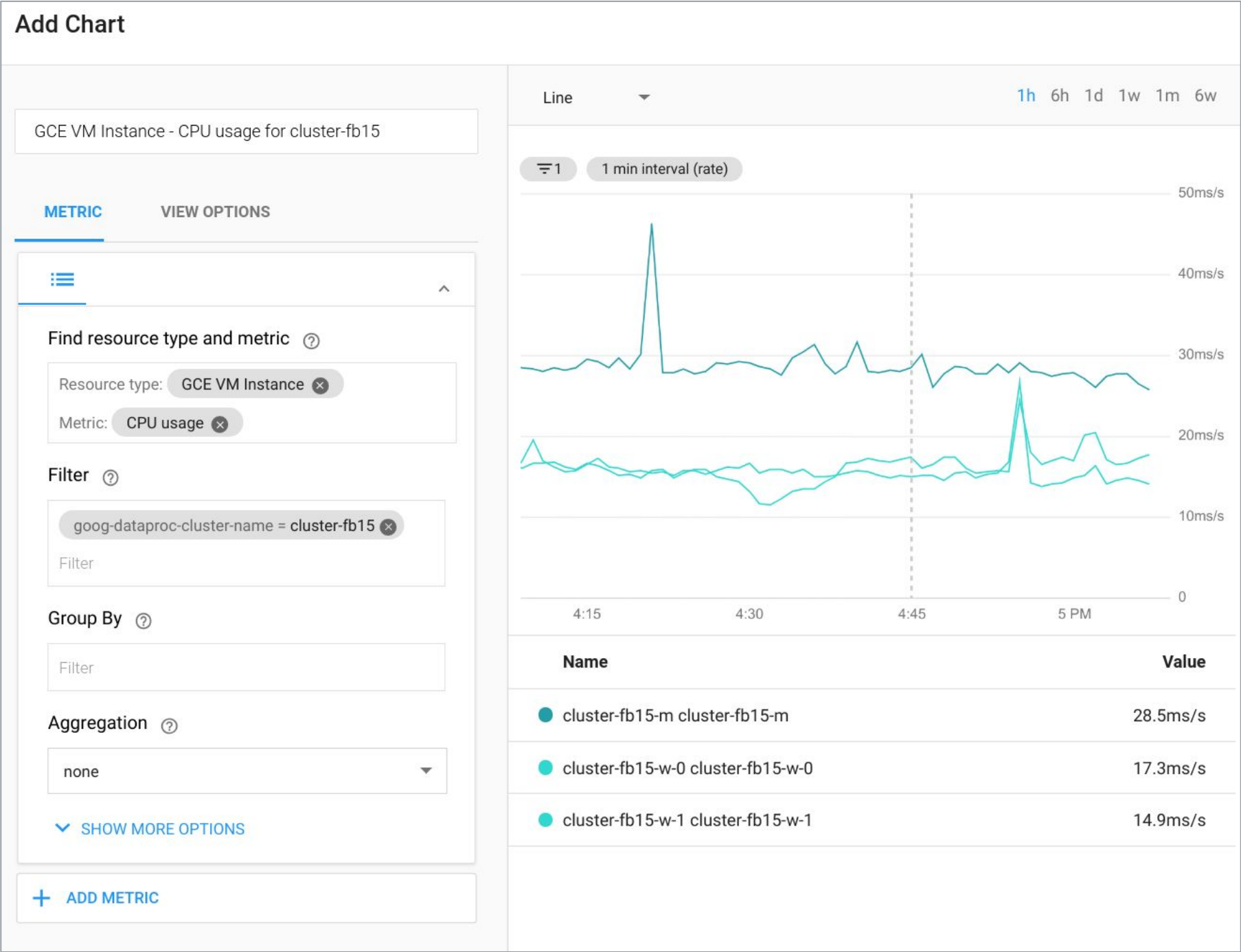
```
gcloud dataproc jobs submit hadoop --driver-log-levels
```

You set the log level for the rest of the application from the Spark context.

For example:

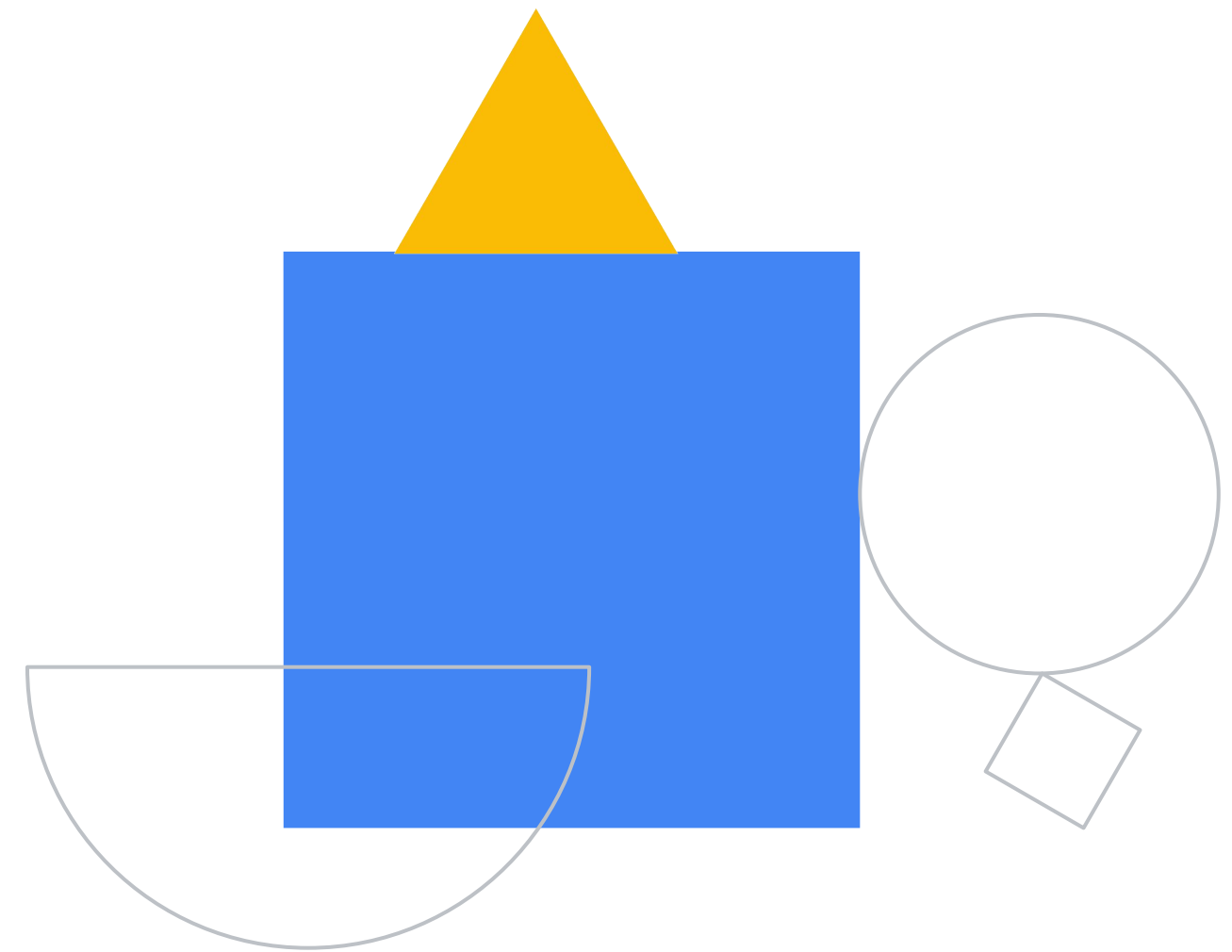
```
spark.sparkContext.setLogLevel("DEBUG")
```

# Monitor your jobs



# Lab Intro

Running Apache Spark jobs  
on Dataproc



# Lab objectives

01

Migrate existing Spark jobs to Dataproc

02

Modify Spark jobs to use Cloud Storage instead of HDFS

03

Optimize Spark jobs to run on Job specific clusters



# Summary

The Hadoop ecosystem

Running Hadoop on Dataproc

Cloud Storage instead of HDFS

Optimizing Dataproc

