Streaming Auto-Scaling in Google Cloud Dataflow

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https://commons.wikimedia.org/wiki/File:Globe_centered_in_the_Atlantic_Ocean_(green_and_grey_globe_scheme).svg

Individual Ranking

Sarah	151,365
Joe	109,903
Milo	98,736

⋮

Team Ranking

	1,251,965
	1,019,341
	989,673

⋮

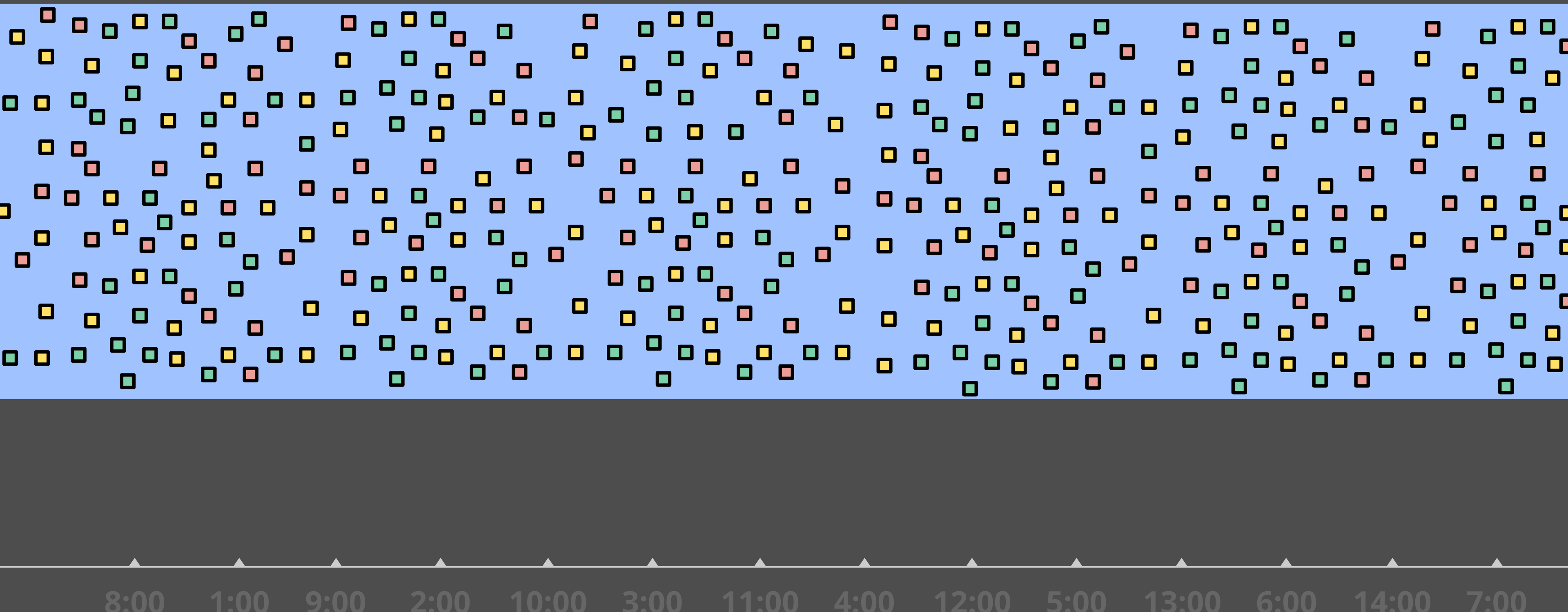
Hourly Ranking

⋮

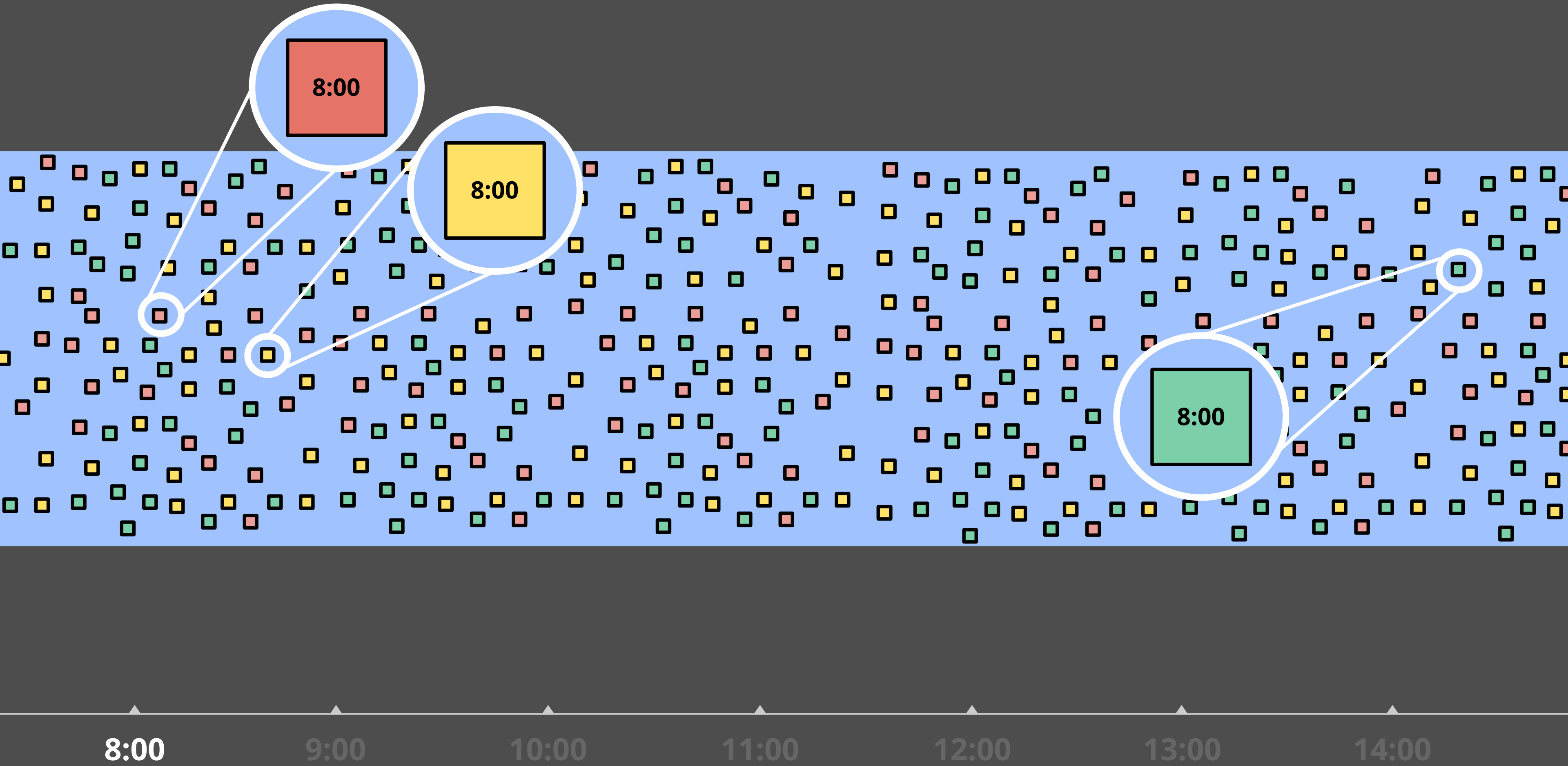
Daily Ranking

⋮

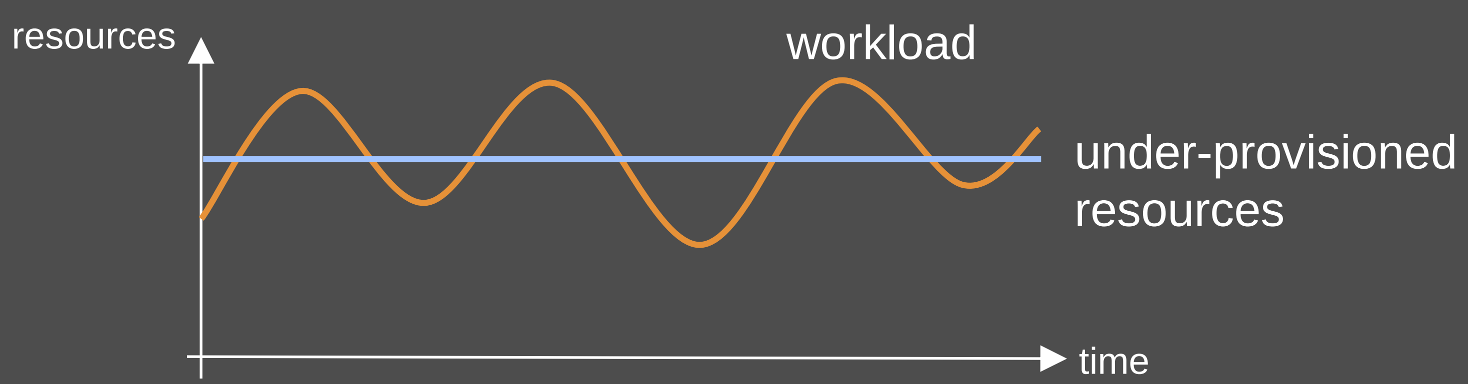
An Unbounded Stream of Game Events



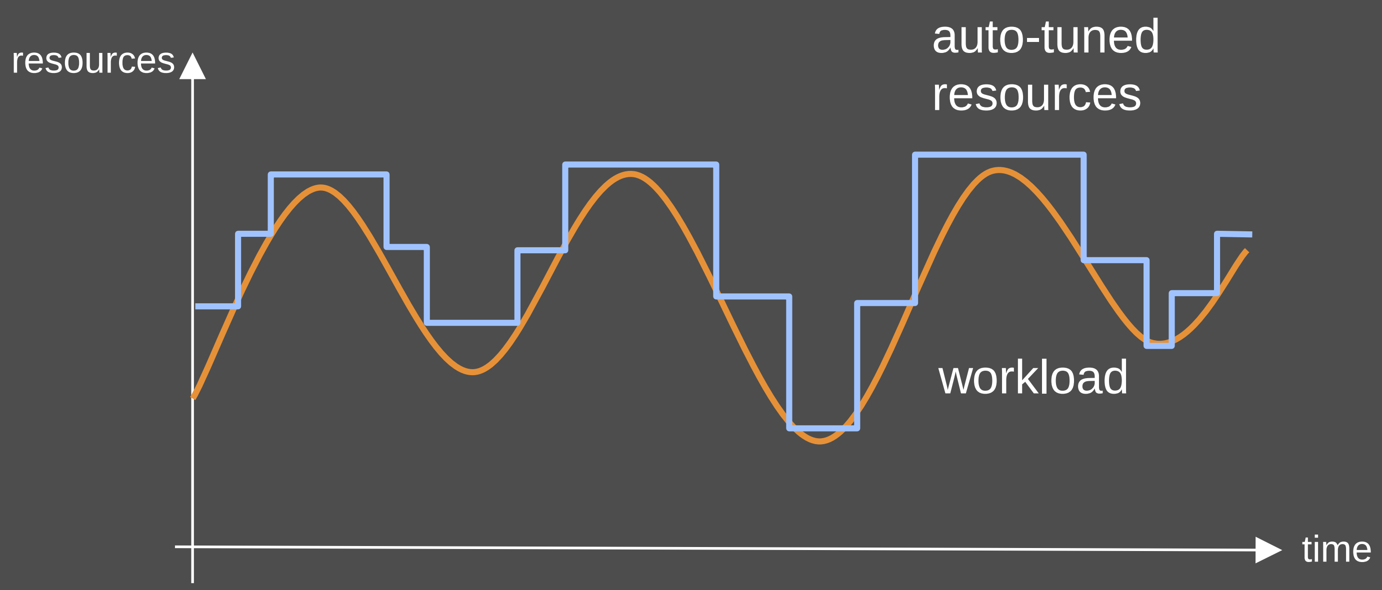
… with unknown delays.



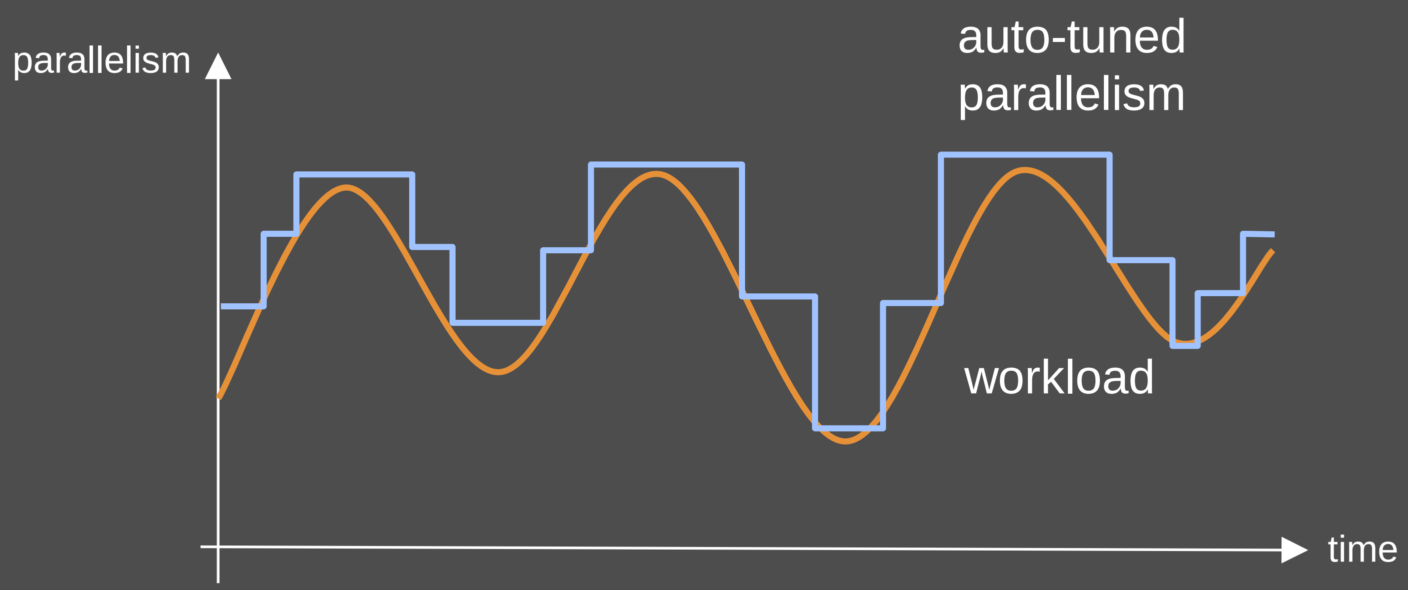
The Resource Allocation Problem



Matching Resources to Workload



Resources = Parallelism



More generally: VMs (including CPU, RAM, network, IO).

Assumptions

Big Data Problem

Embarrassingly Parallel

Scaling VMs ==> Scales Throughput

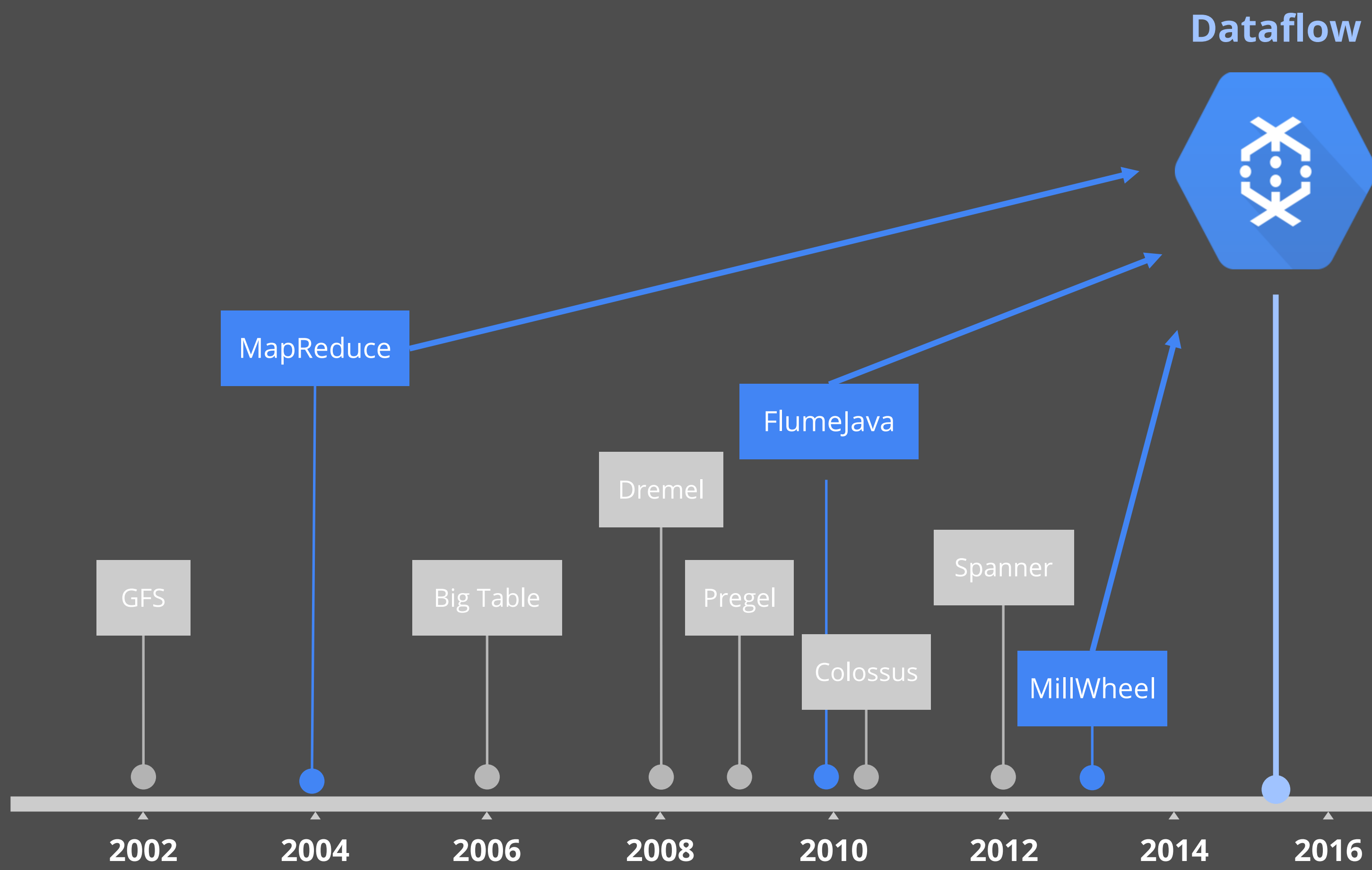
Horizontal Scaling

Agenda

1. Streaming Dataflow Pipelines
2. Pipeline Execution
3. Adjusting Parallelism Automatically
4. Summary + Future Work

1 Streaming Dataflow

Google's Data-Related Systems



Google Dataflow SDK

Open Source SDK used to construct a Dataflow pipeline.

(Now Incubating as Apache Beam)

Computing Team Scores

```
// Collection of raw log lines
PCollection<String> raw = ...;

// Element-wise transformation into team/score
// pairs
PCollection<KV<String, Integer>> input =
    raw.apply(ParDo.of(new ParseFn()))

// Composite transformation containing an
// aggregation
PCollection<KV<String, Integer>> output = input
  .apply(Window.into(FixedWindows.of(Minutes(60))))
  .apply(Sum.integersPerKey());
```

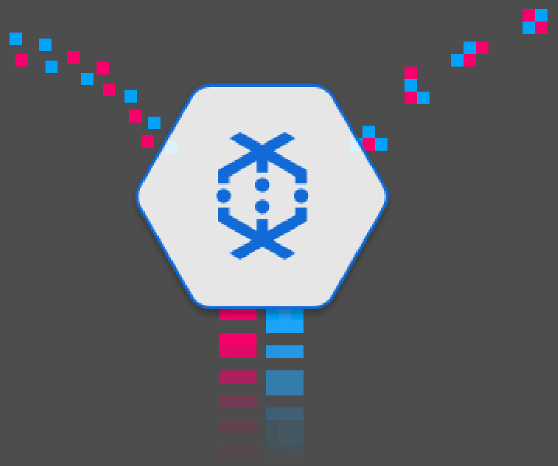
Google Cloud Dataflow

- Given code in Dataflow (incubating as Apache Beam) SDK...

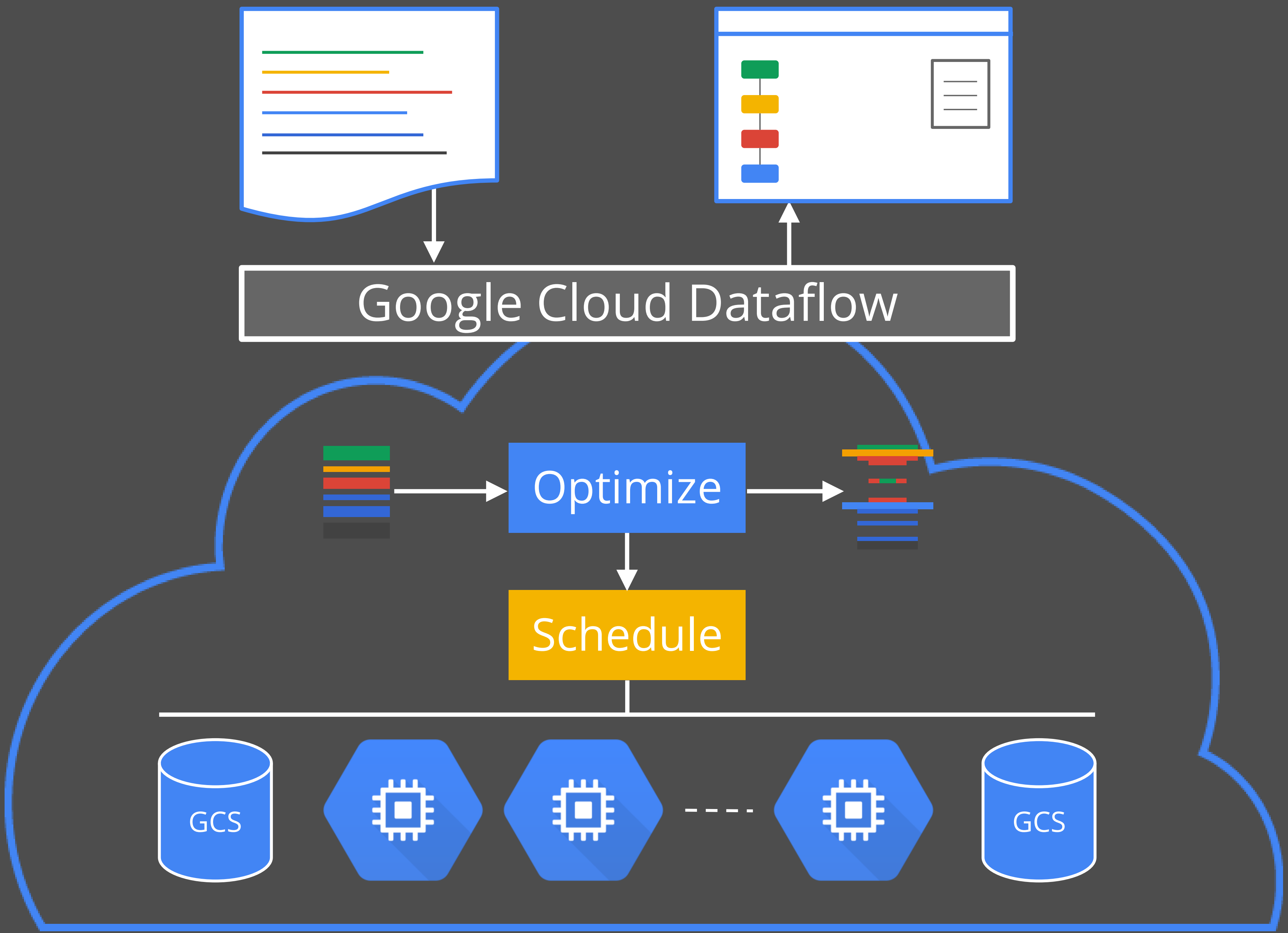
- Pipelines can run…
  - On your development machine
  - On the Dataflow Service on Google Cloud Platform
  - On third party environments like Spark or Flink.

Google Cloud Dataflow

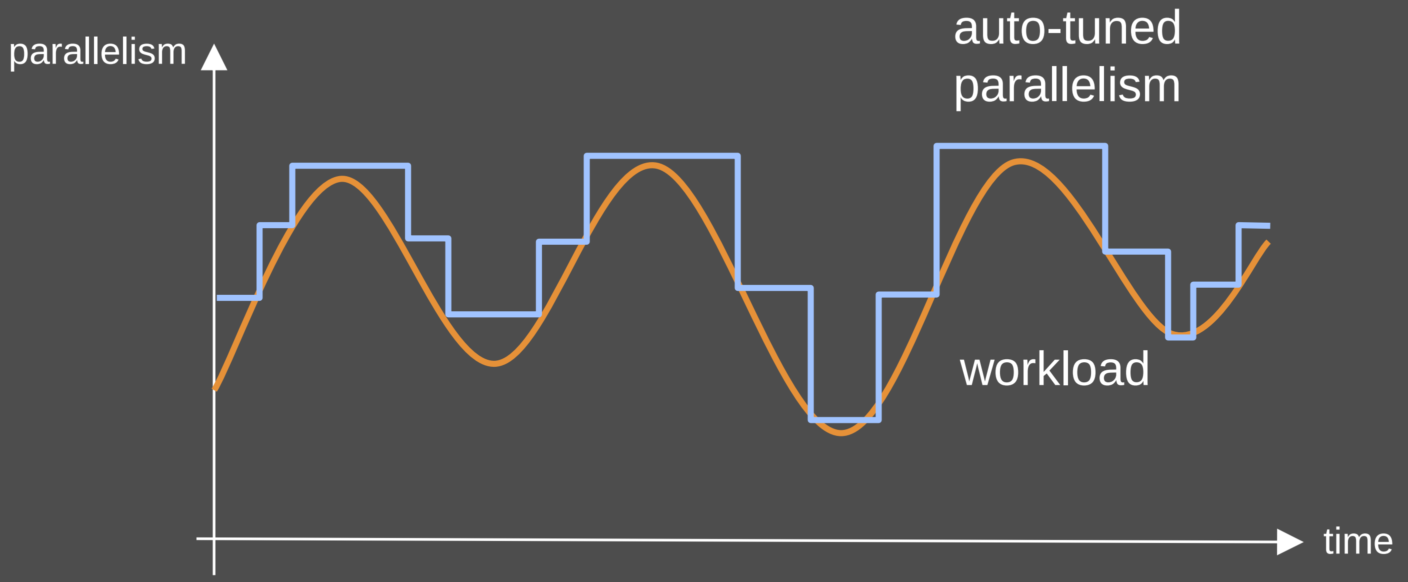
Google Cloud Platform



A fully-managed cloud service and programming model for batch and streaming big data processing.


Google Cloud Dataflow
Optimize
Schedule
GCS
GCS

Back to the Problem at Hand



Auto-Tuning Ingredients

Signals measuring Workload

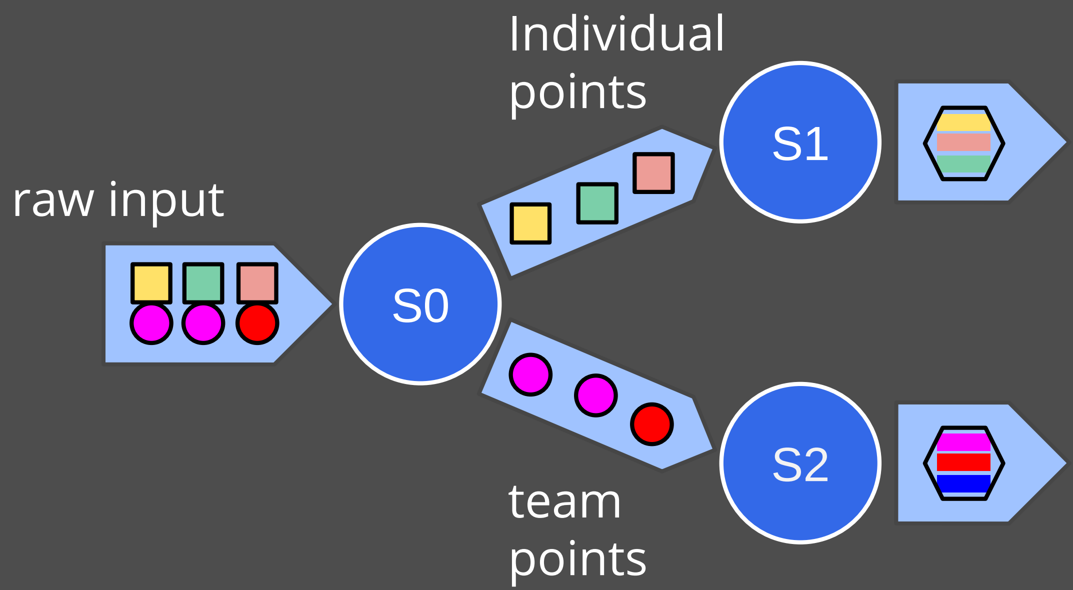
Policy making Decisions

Mechanism actuating Change

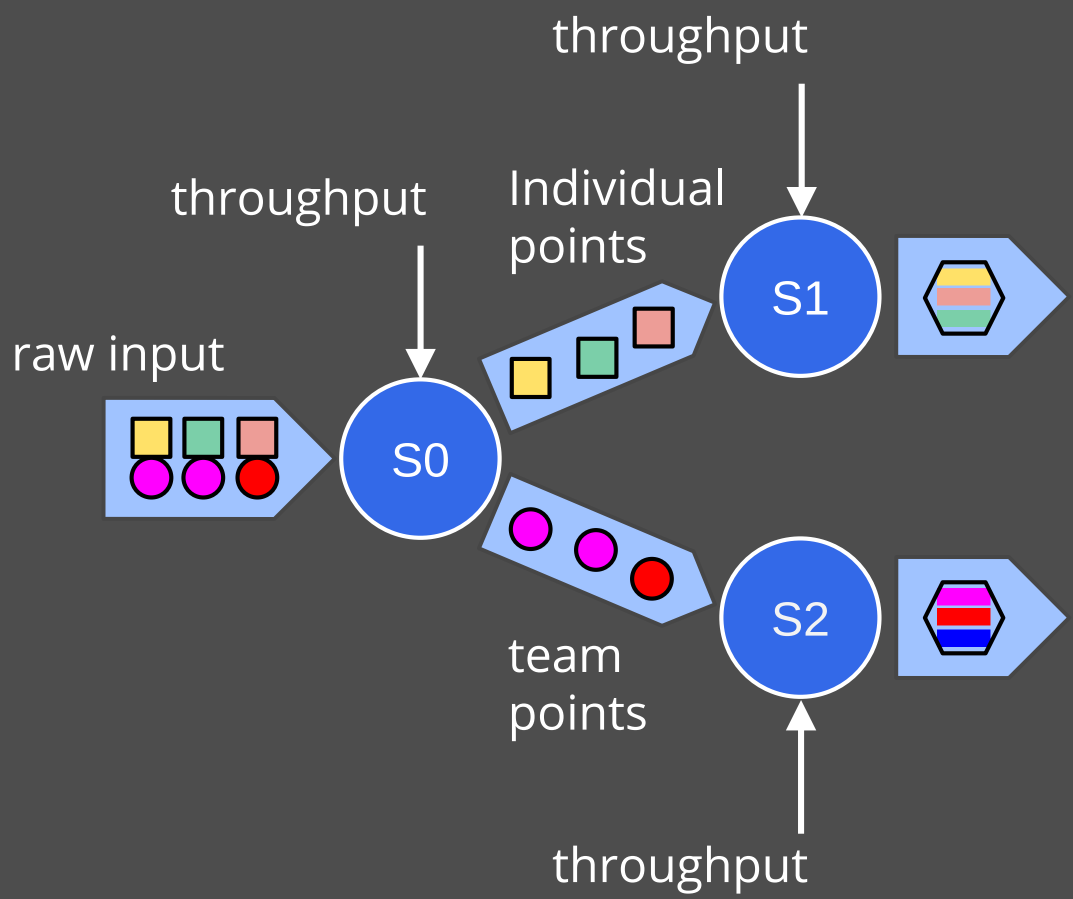
2

Pipeline Execution

Optimized Pipeline = DAG of Stages

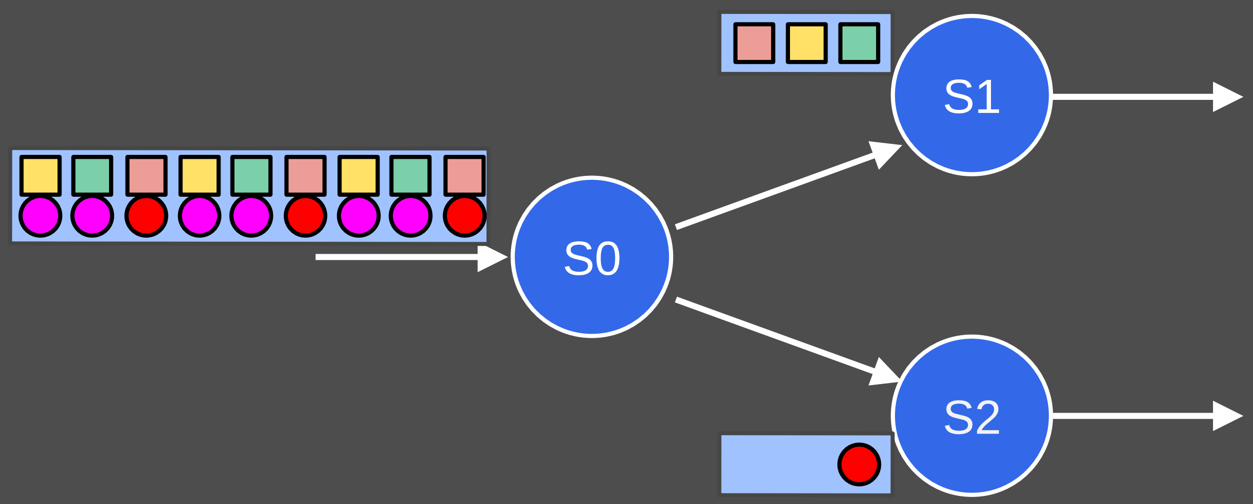


Stage Throughput Measure



Picture by Alexandre Duret-Lutz, Creative Commons 2.0 Generic

Queues of Data Ready for Processing



Queue Size = Backlog

Backlog Size

vs.

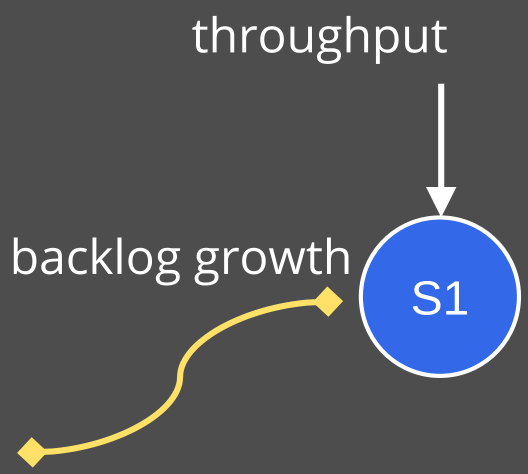
Backlog Growth

Backlog Growth

=

Processing Deficit

Derived Signal: Stage Input Rate



Input Rate = Throughput + Backlog Growth

Constant Backlog…

…could be bad

$$\text{Backlog Time} = \frac{\text{Backlog Size}}{\text{Throughput}}$$

Backlog Time =

Time to get through backlog

Bad Backlog = Long Backlog Time

Backlog Growth
and
Backlog Time
Inform Upscaling.

What Signals indicate
Downscaling?

Low CPU Utilization

Signals Summary

Throughput

Backlog growth

Backlog time

CPU utilization

Policy: making Decisions

Goals:

1. No backlog growth
2. Short backlog time
3. Reasonable CPU utilization

Upscaling Policy: Keeping Up

Given M machines

For a stage, given:

average stage throughput T

average positive backlog growth G of stage

Machines needed for stage to keep up:

$$M' = M \frac{(T + G)}{T}$$

Upscaling Policy: Catching Up

Given M machines

Given R (time to reduce backlog)

For a stage, given:

average backlog time B

Extra machines to remove backlog:

$$Extra = M \frac{B}{R}$$

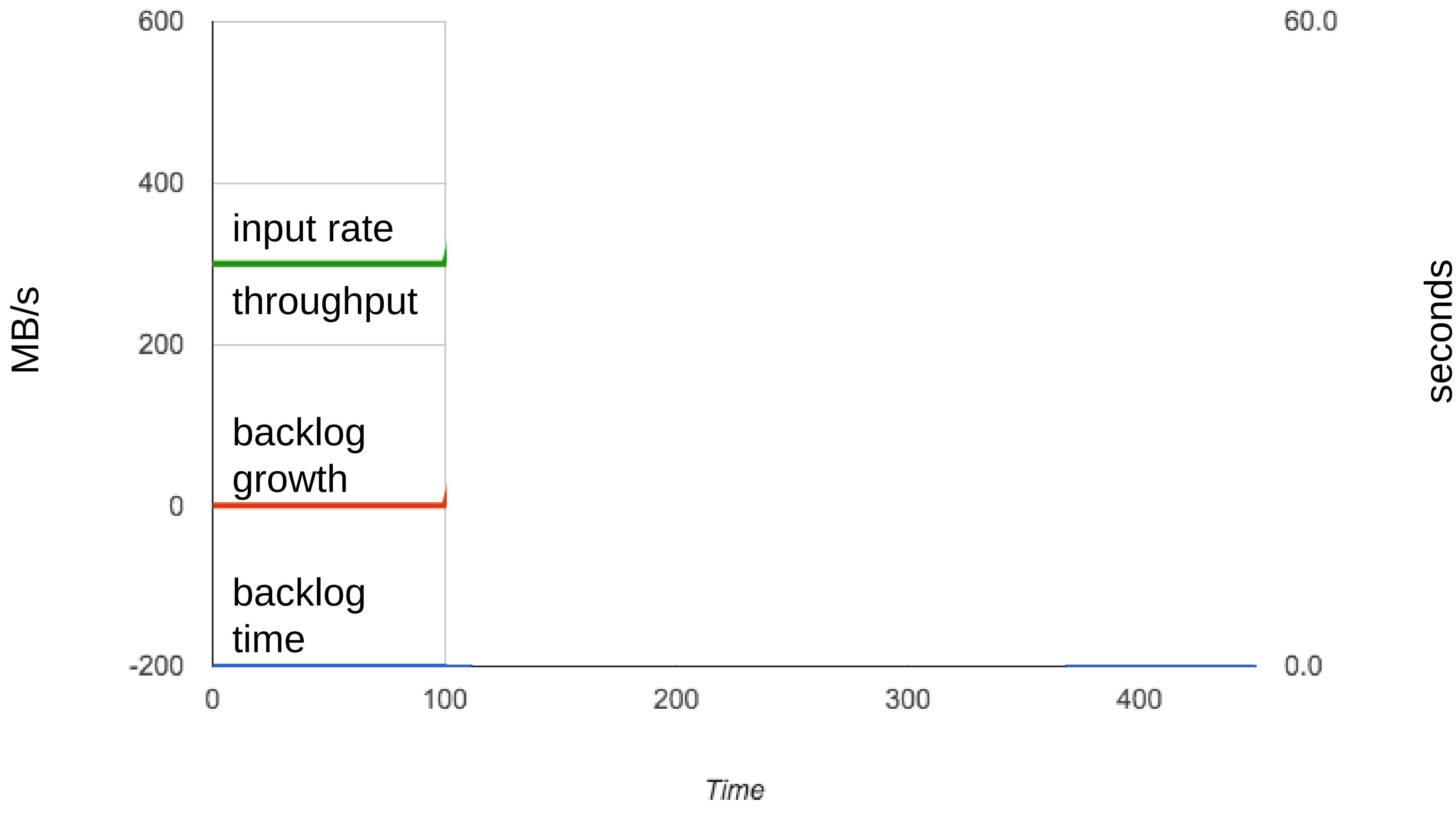
Upscaling Policy: All Stages

Want all stages to:

1. keep up
2. have log backlog time

Pick Maximum over all stages of $M' + Extra$

Example (signals)



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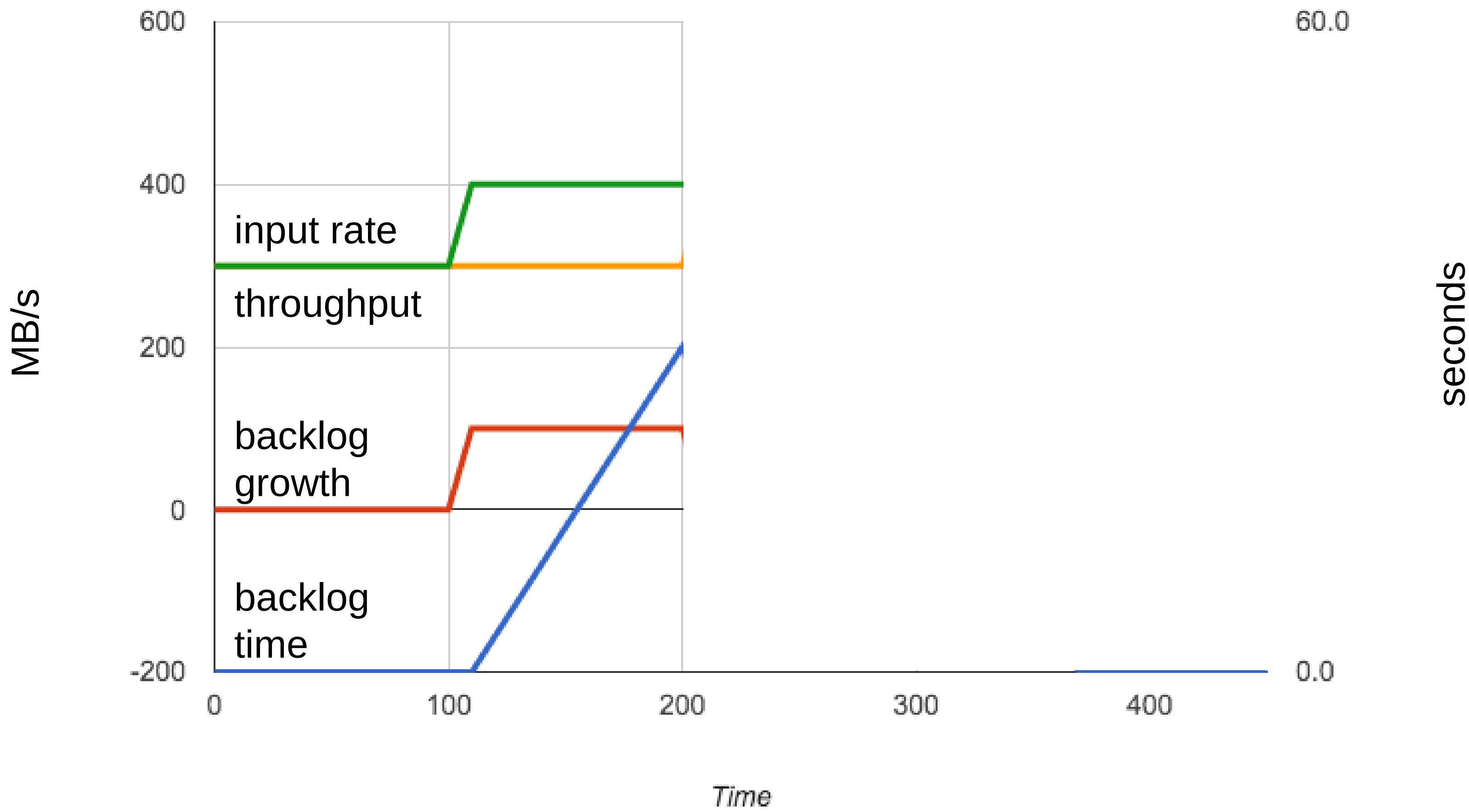

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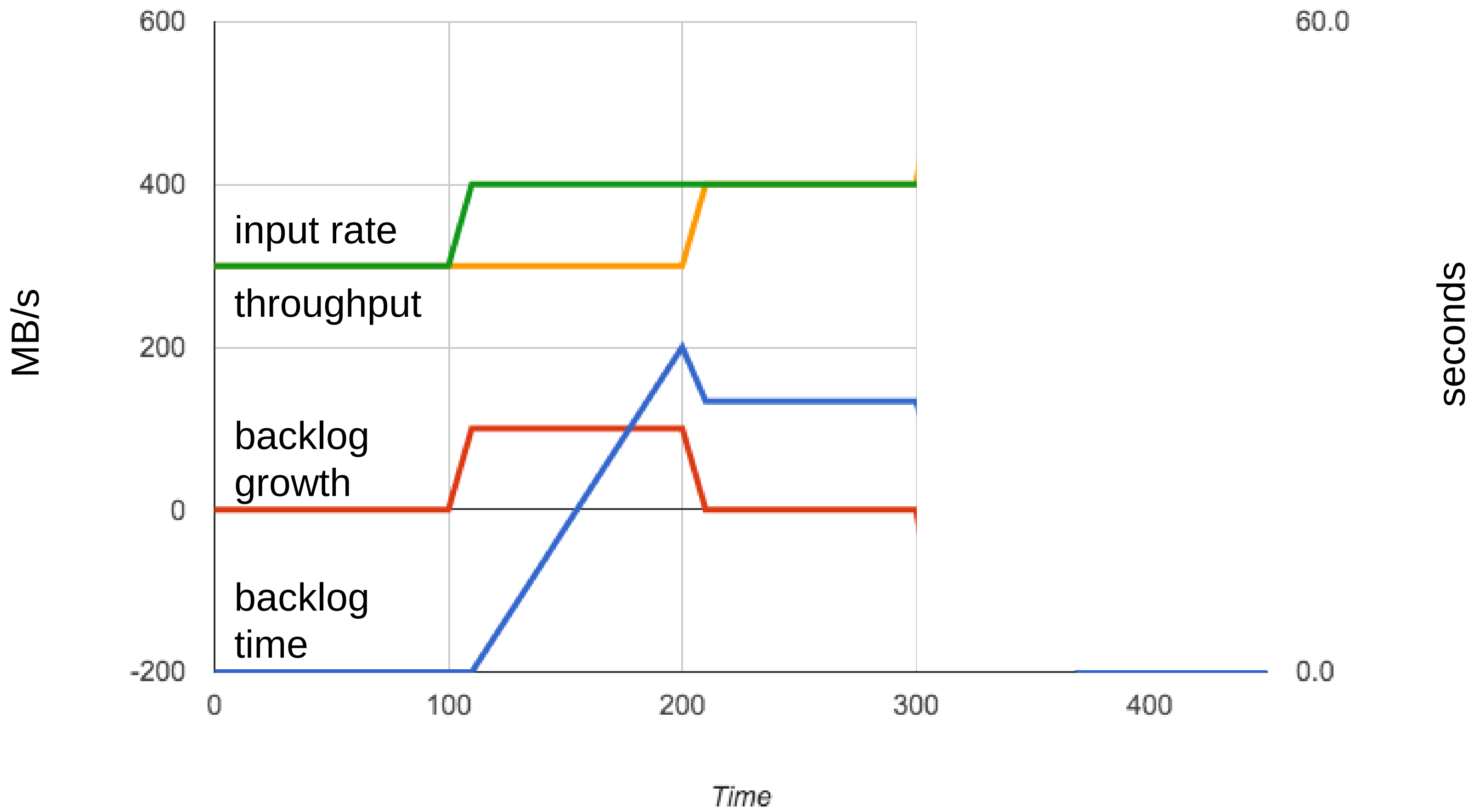

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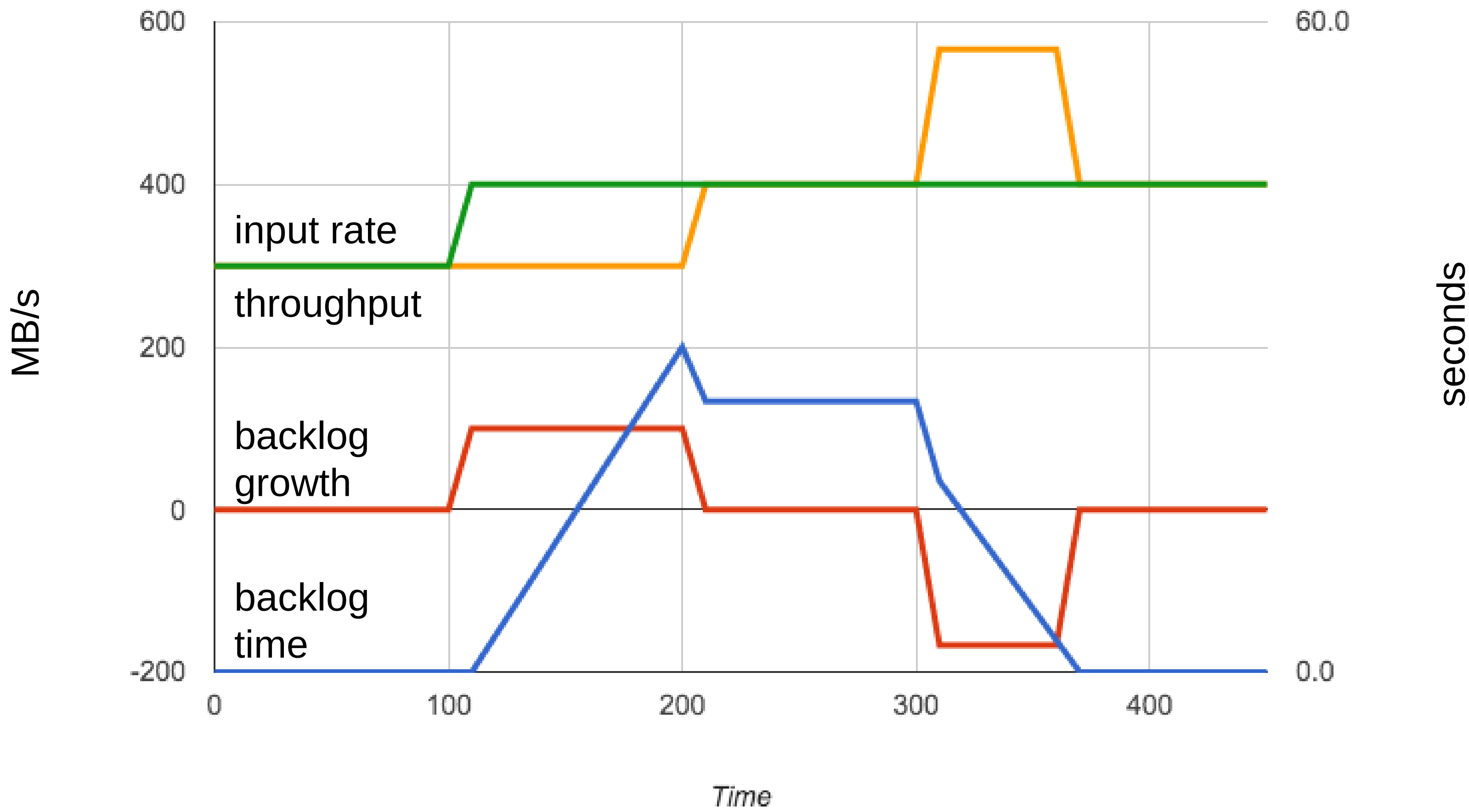
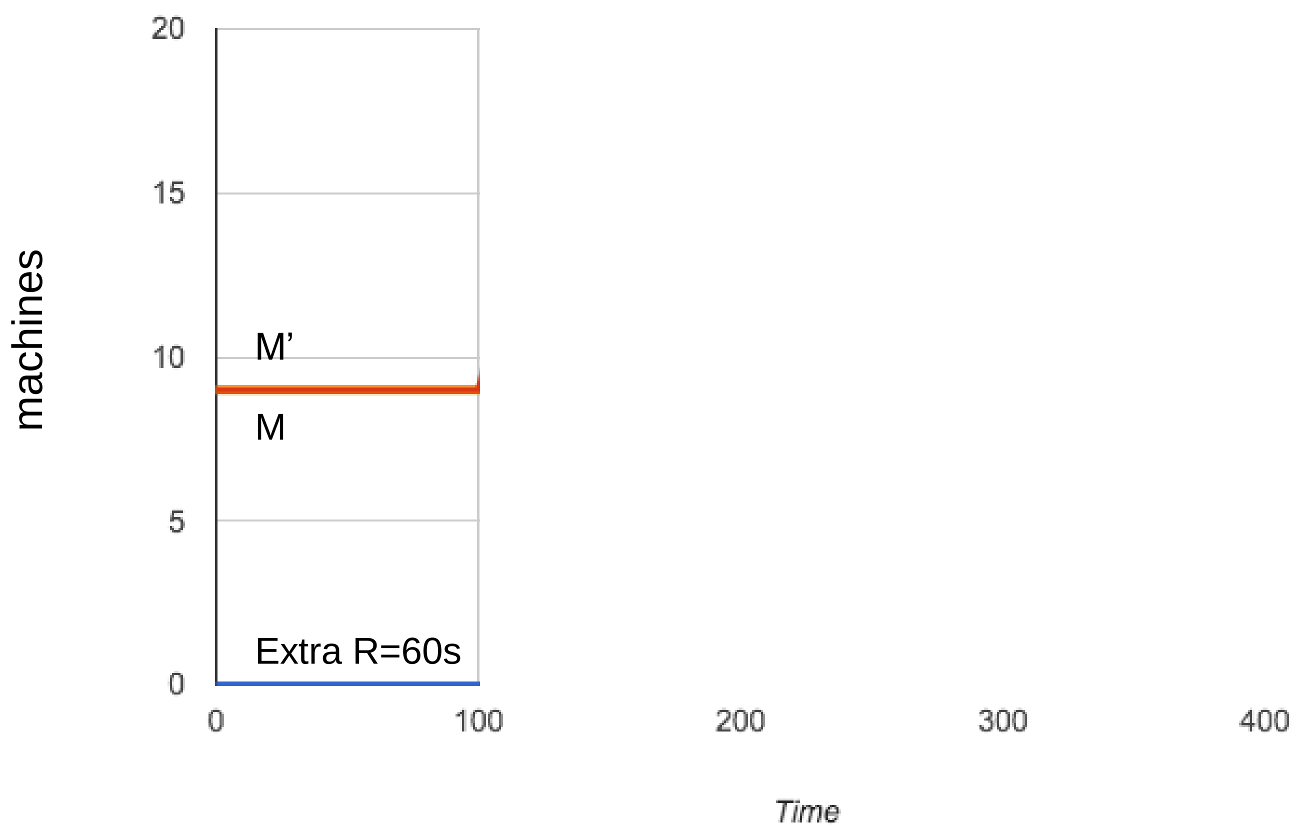


Example (policy)



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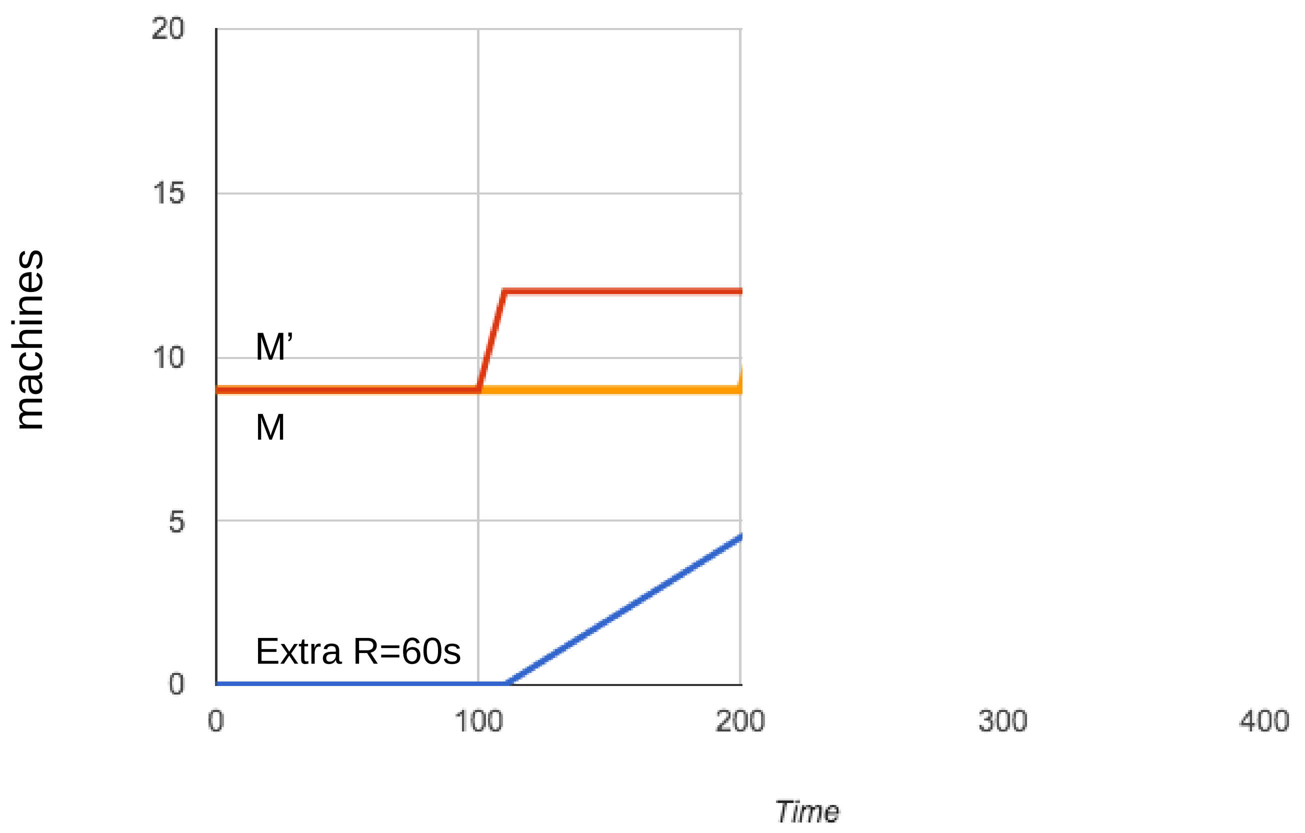

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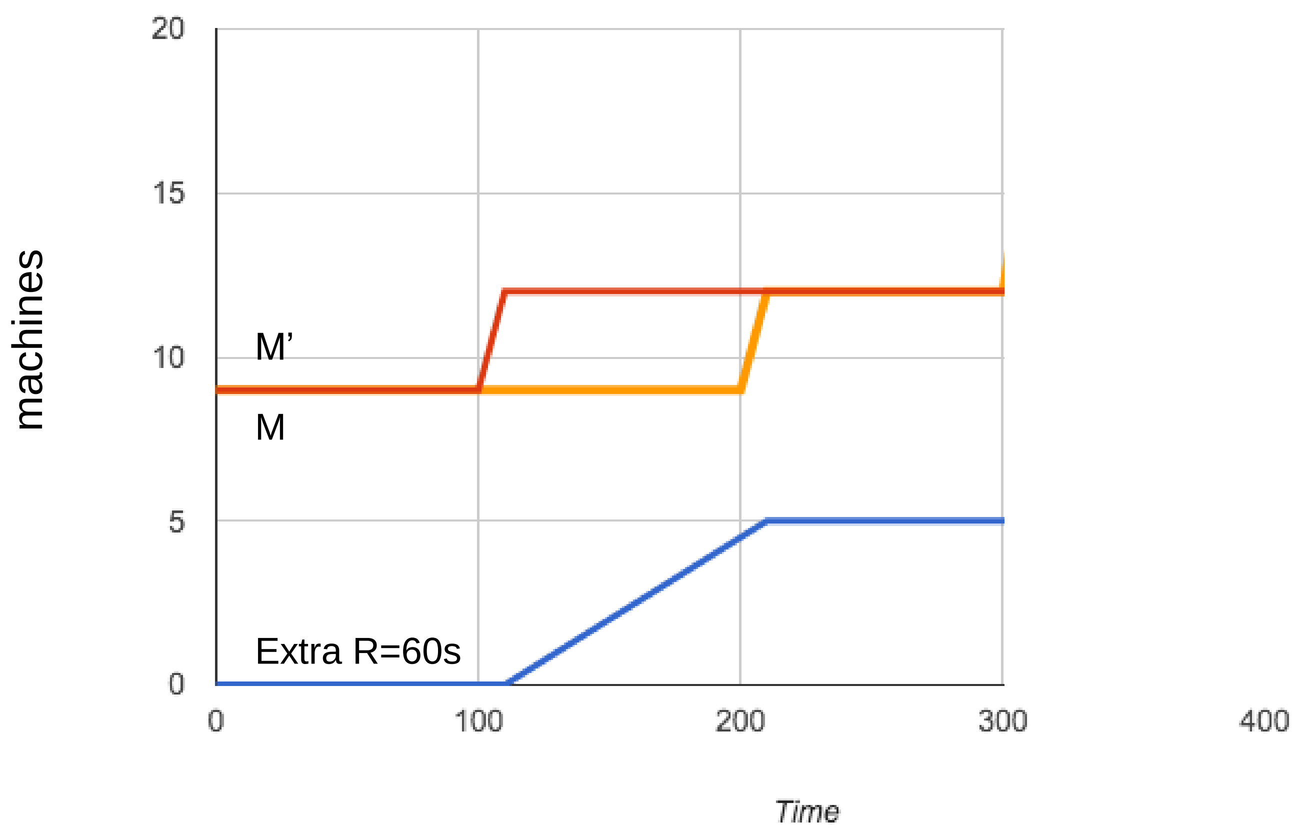
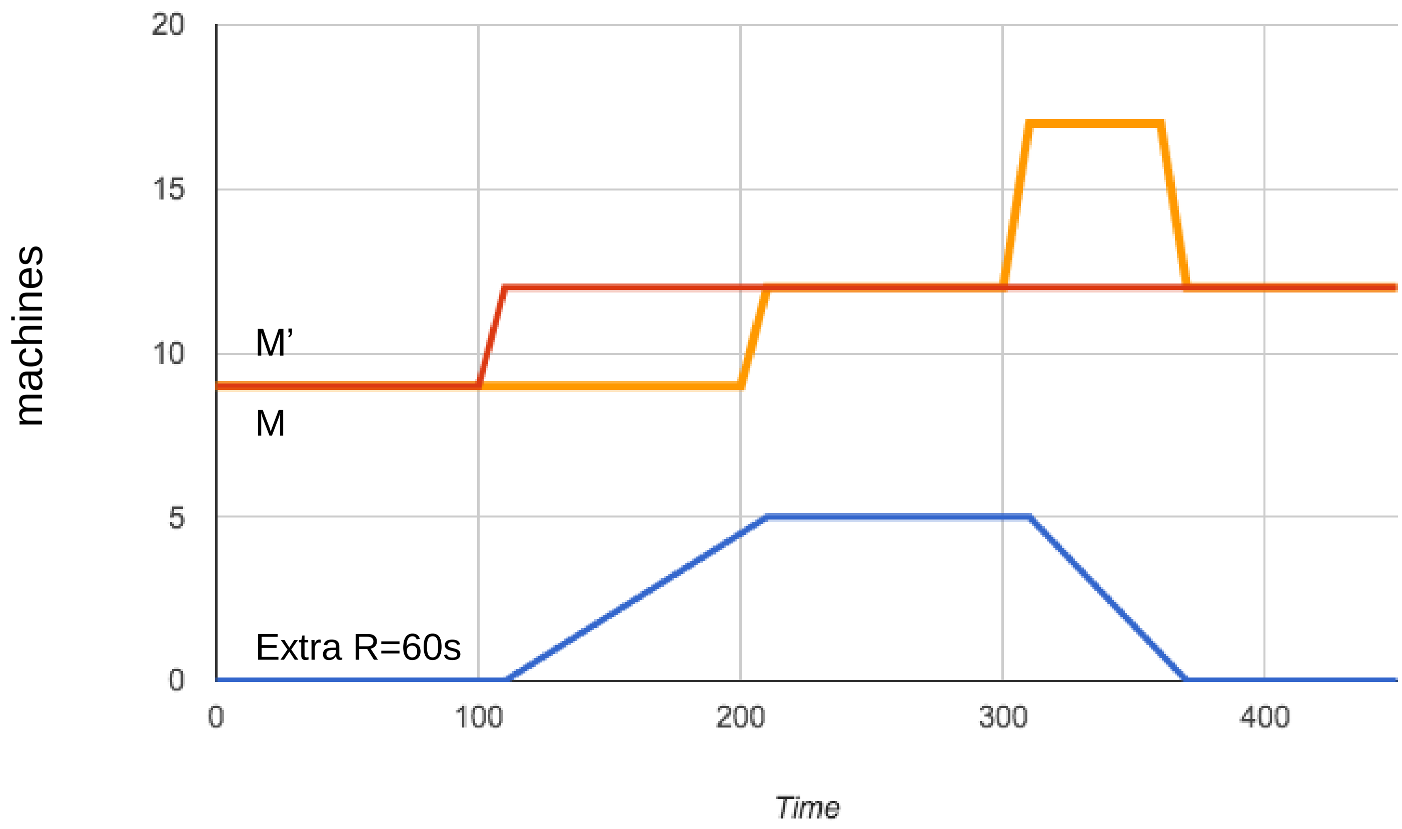


Example (policy)



Preconditions for Downscaling

Low backlog time

No backlog growth

Low CPU utilization

How far can we downscale?

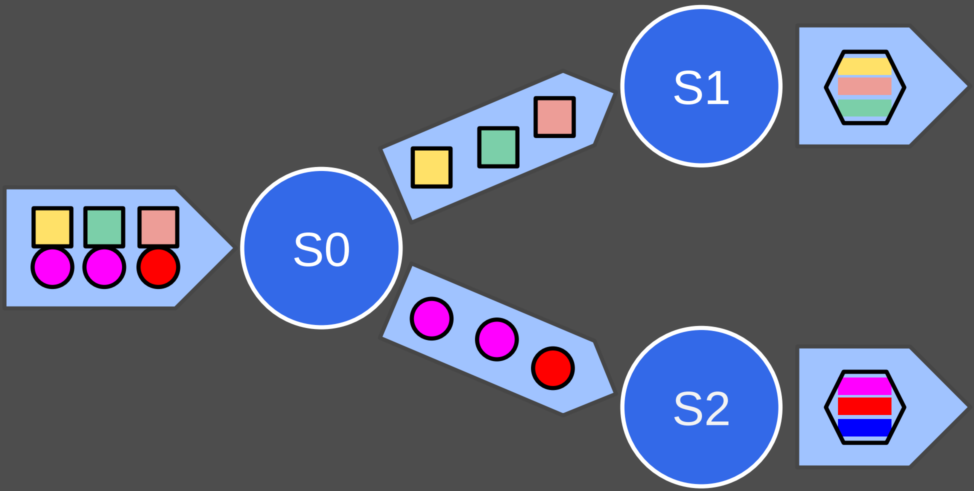
Stay tuned...

Mechanism: actuating Change

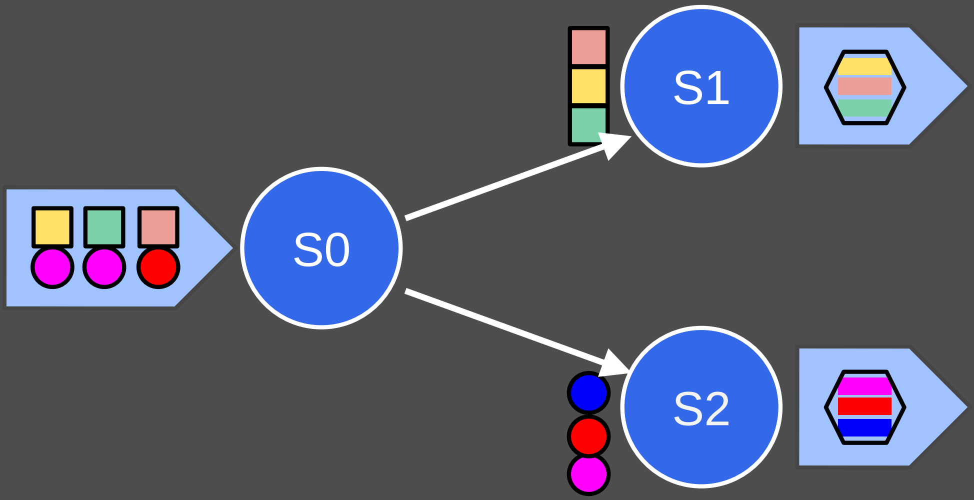
3

Adjusting Parallelism of a Running Streaming Pipeline

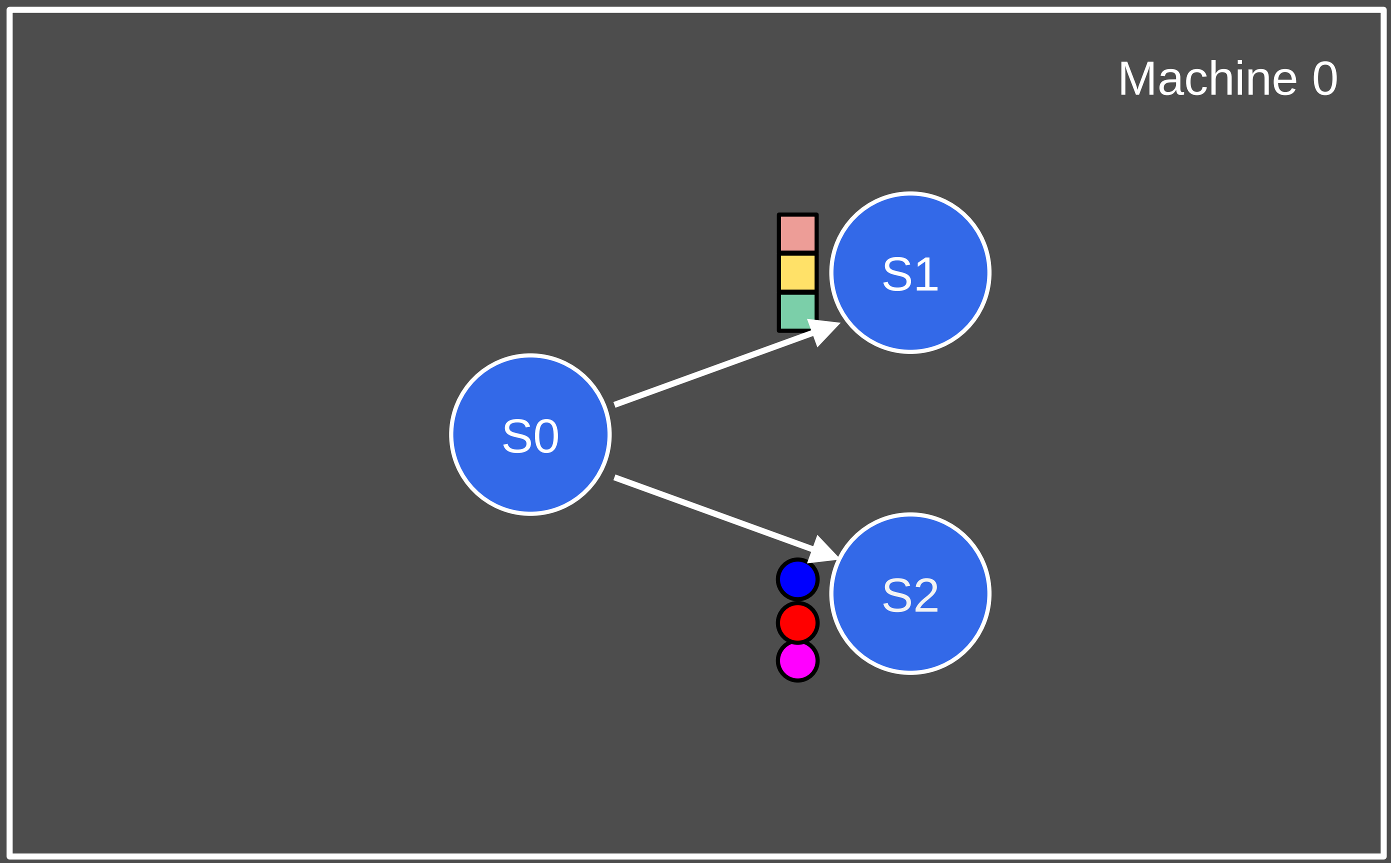
Optimized Pipeline = DAG of Stages



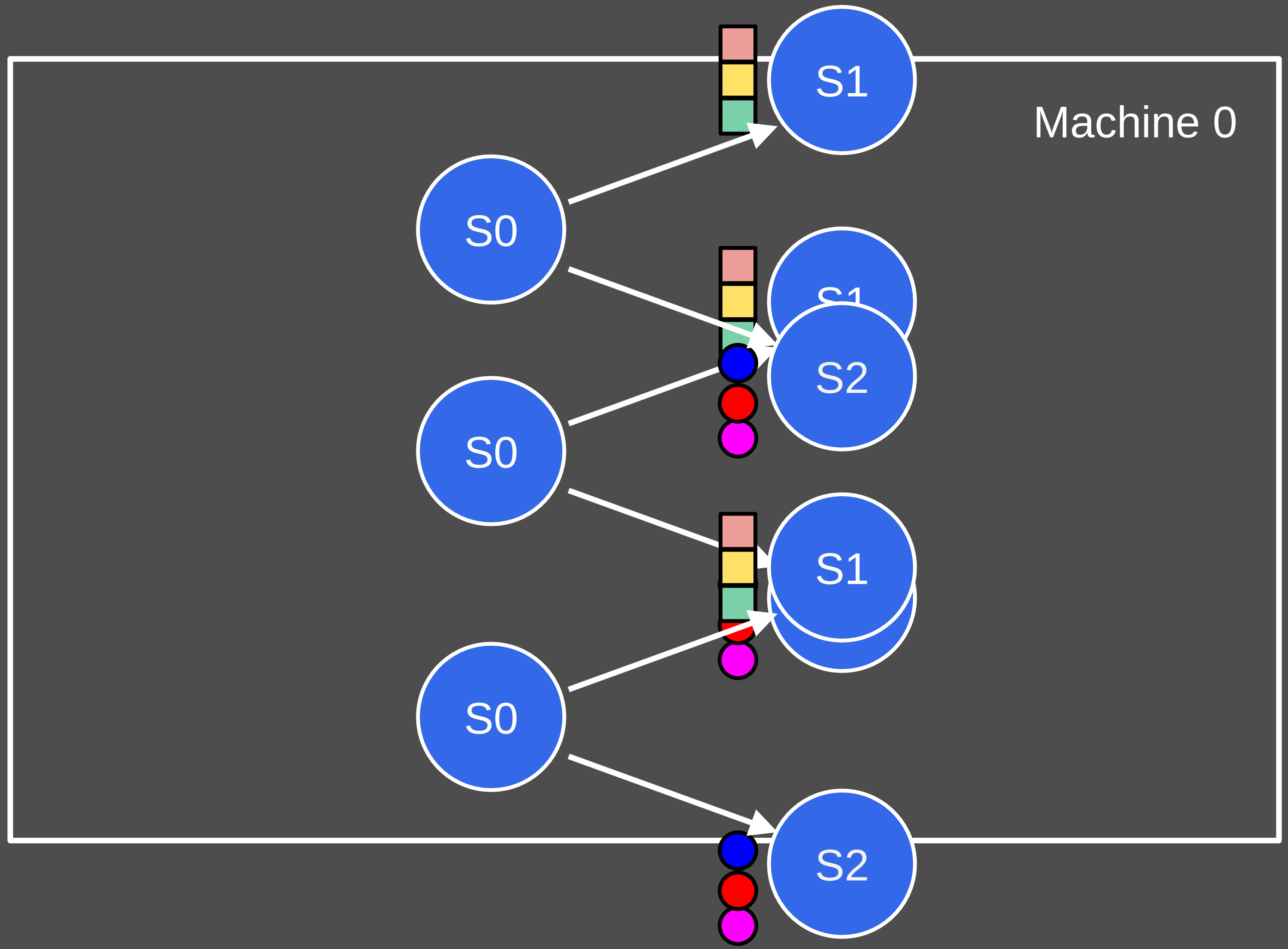
Optimized Pipeline = DAG of Stages



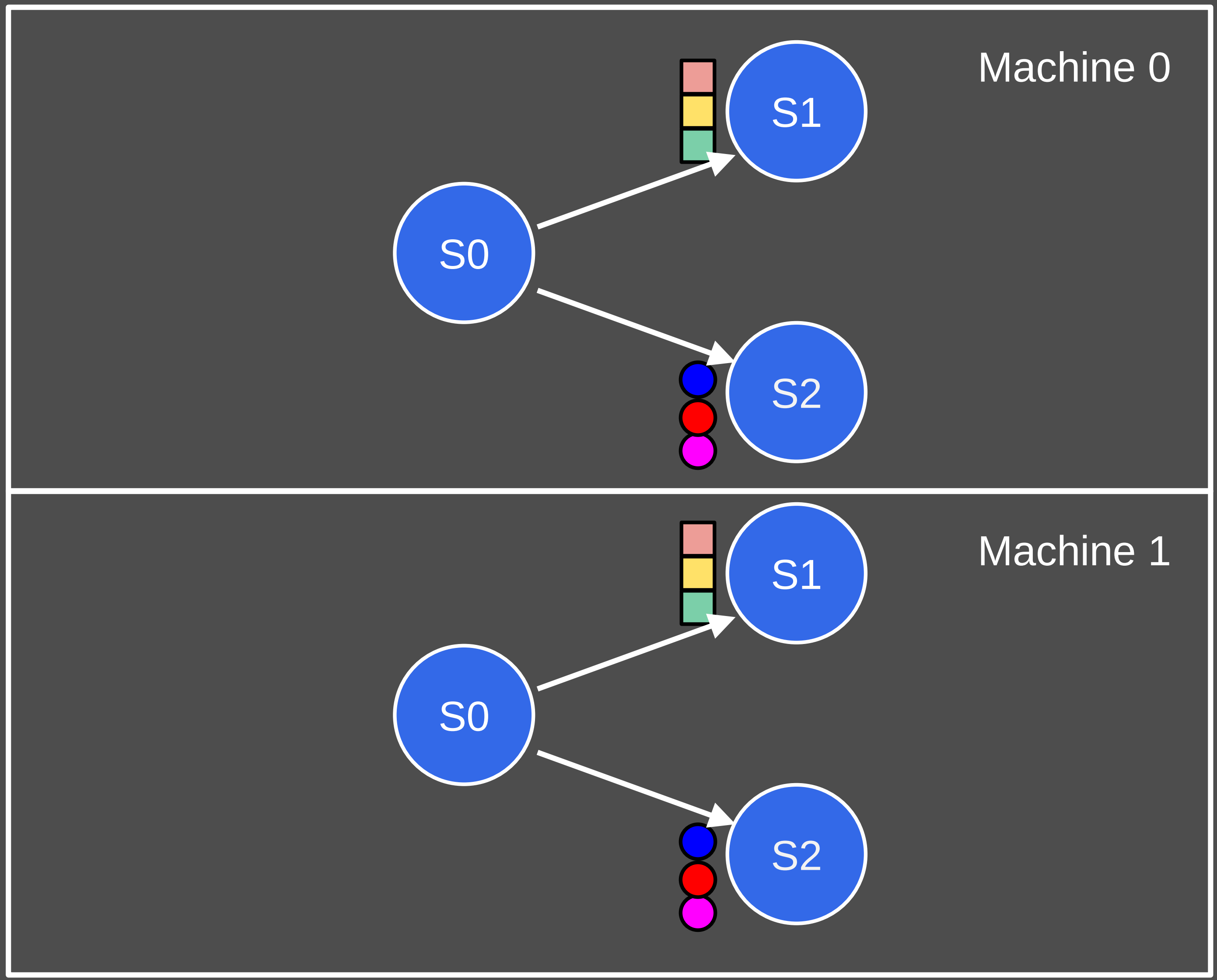
Optimized Pipeline = DAG of Stages



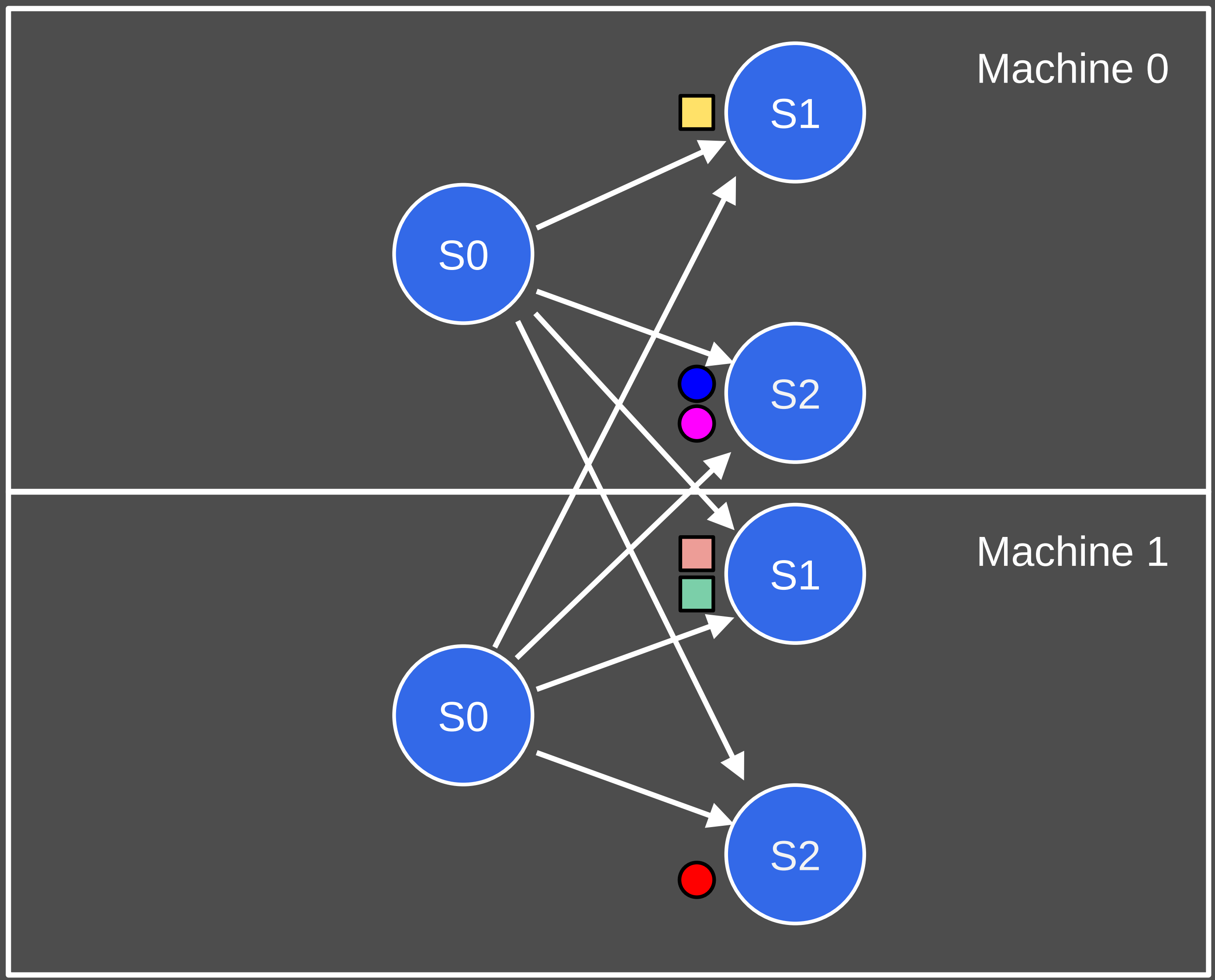
Adding Parallelism



Adding Parallelism

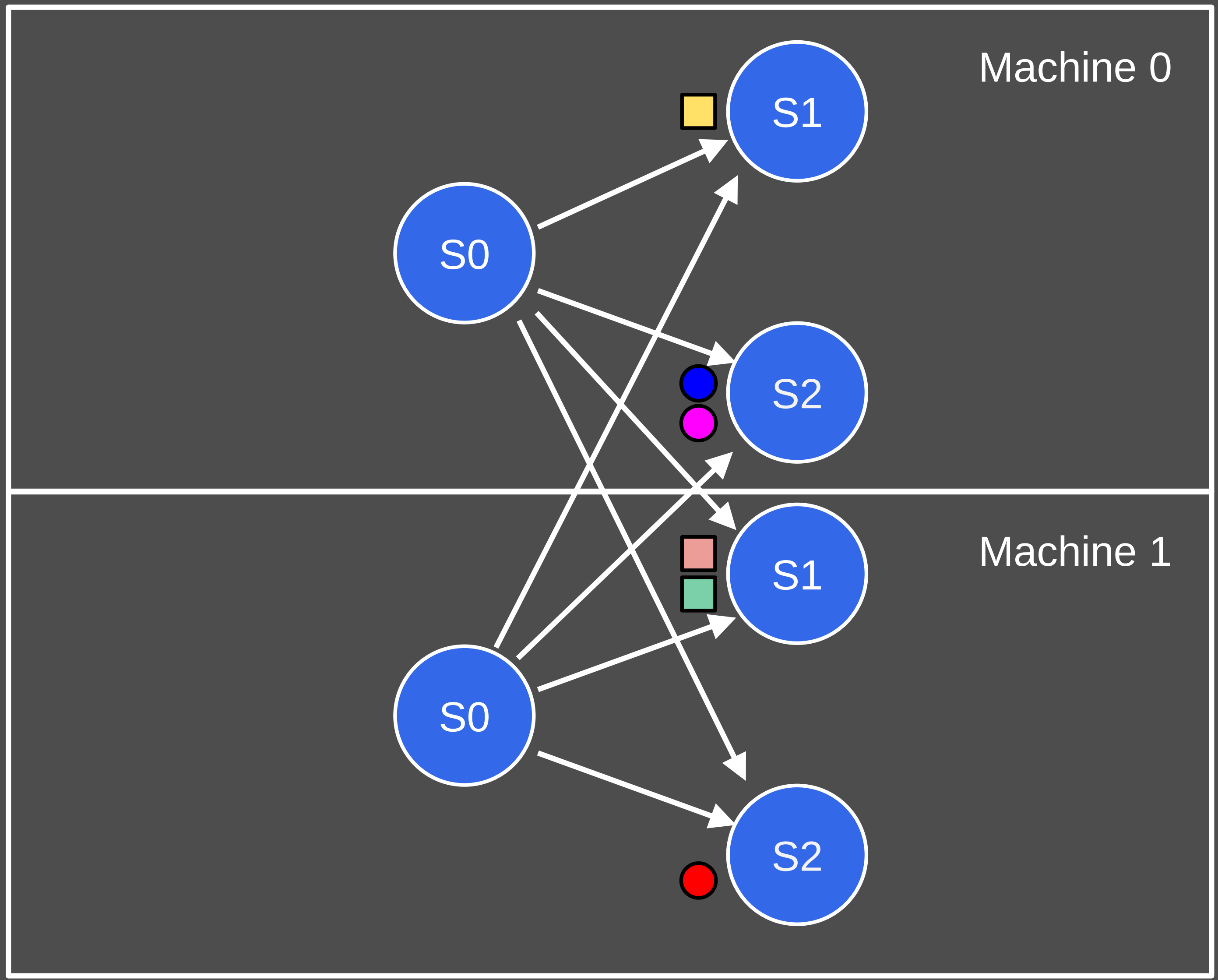


Adding Parallelism = Splitting Key Ranges



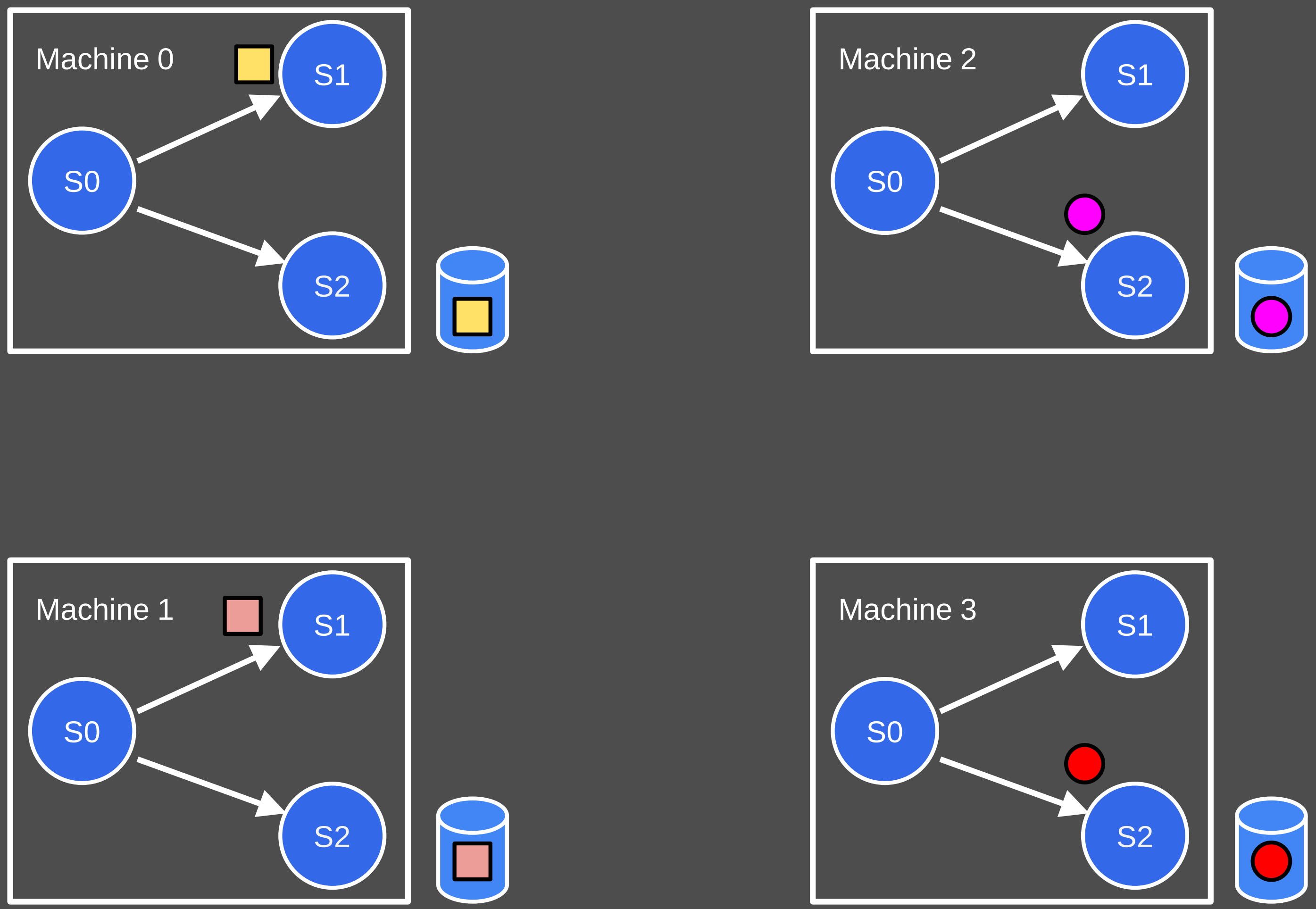
Migrating a Computation

Adding Parallelism = Migrating Computation Ranges

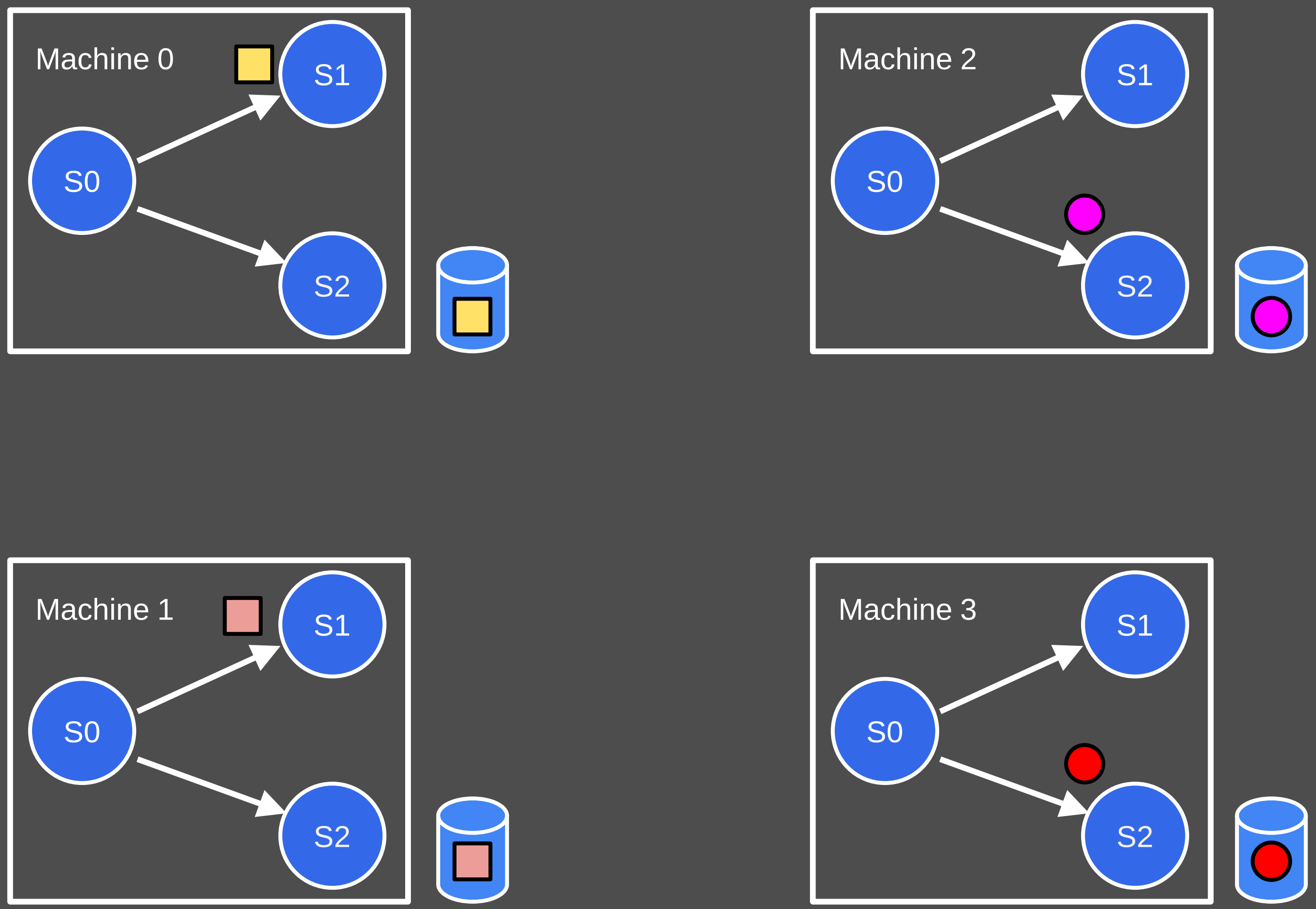


Checkpoint and Recovery
~
Computation Migration

Key Ranges and Persistence



Downscaling from 4 to 2 Machines



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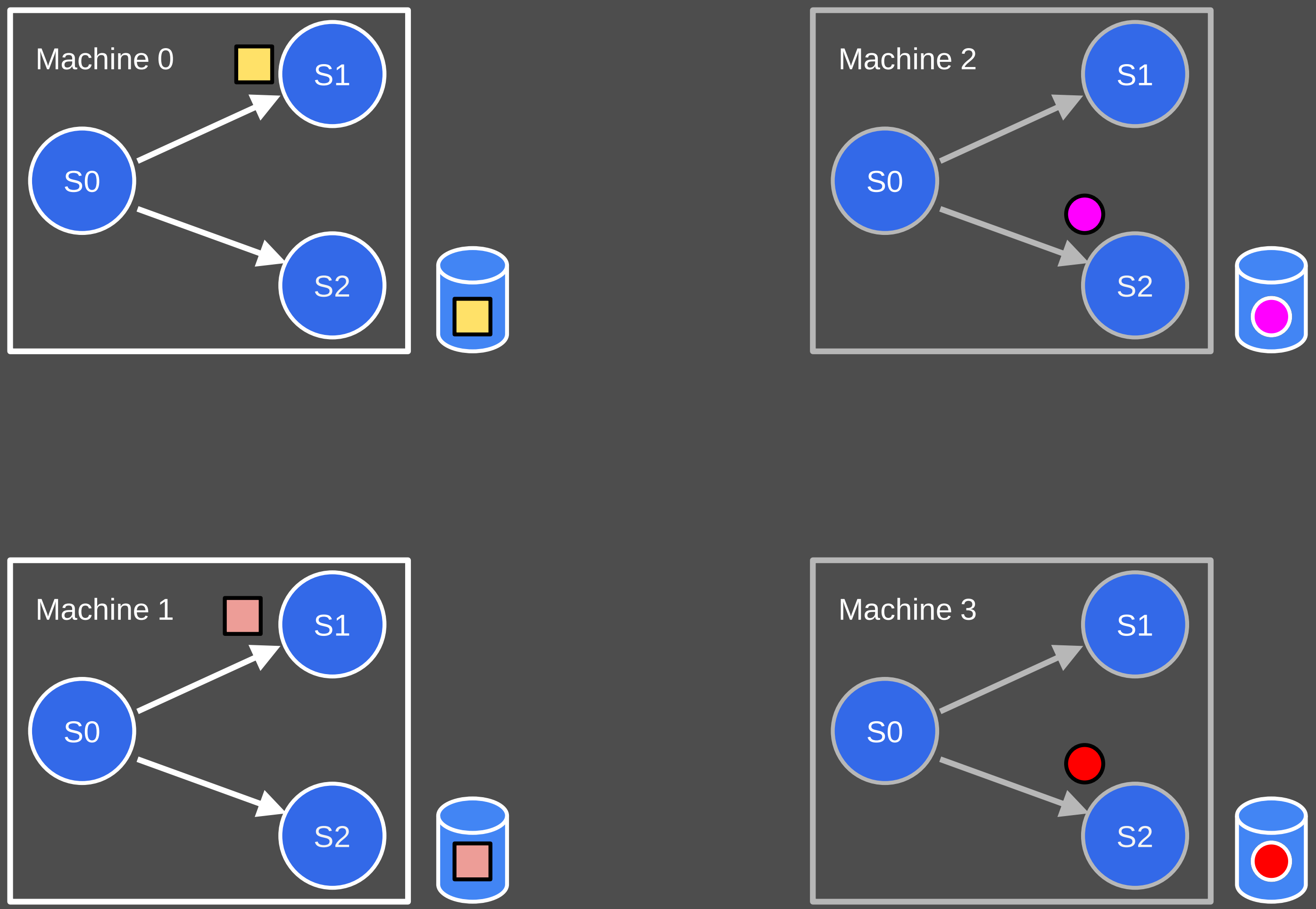

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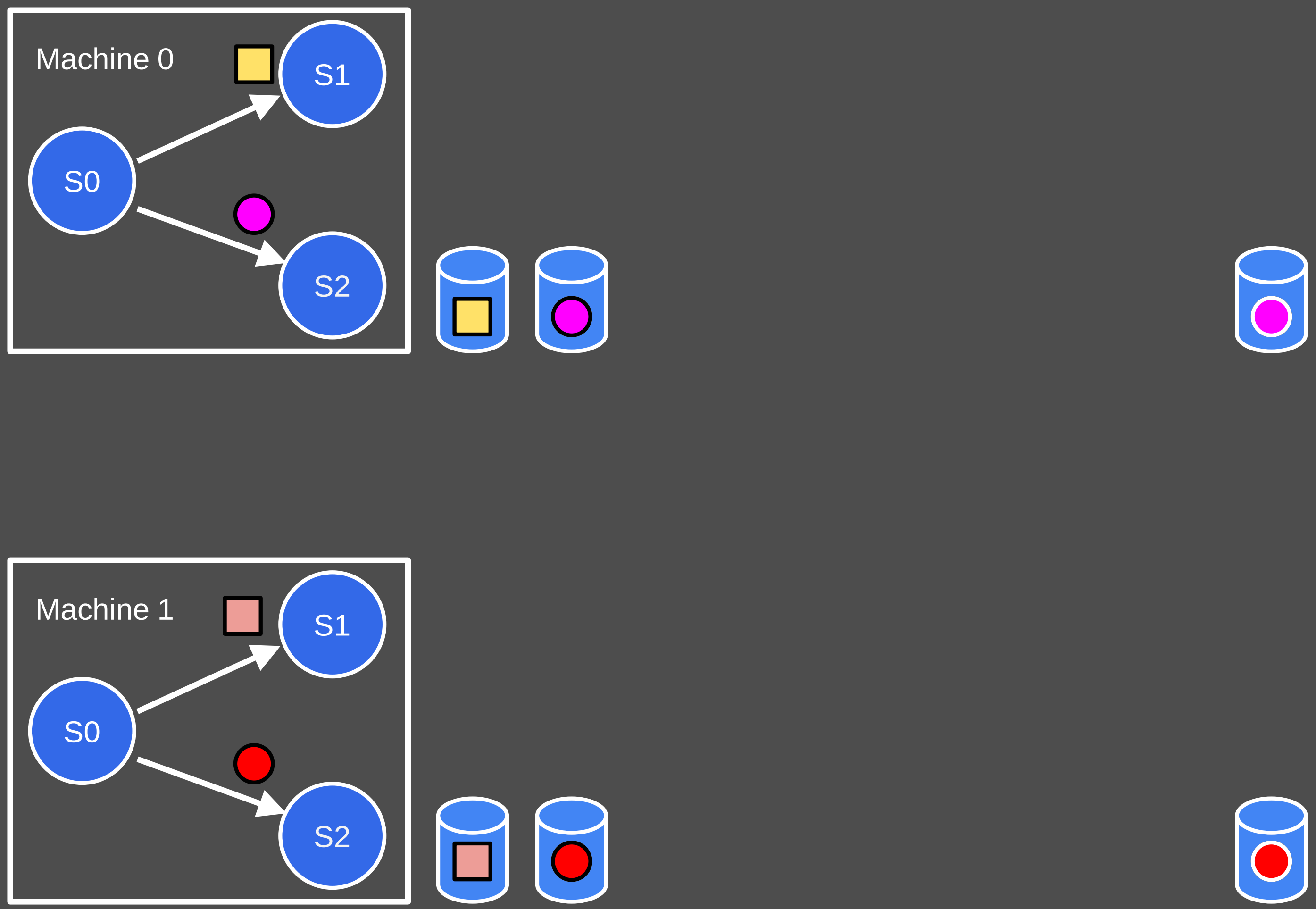

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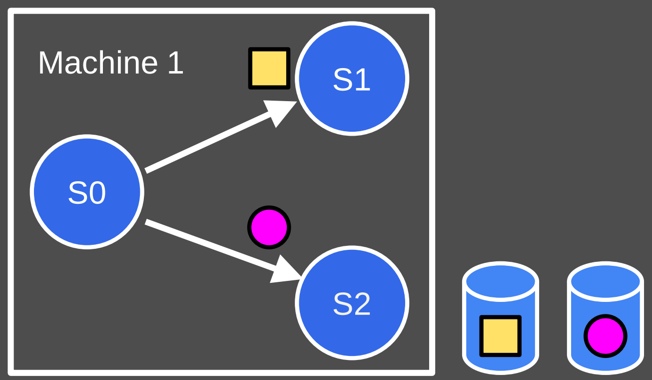
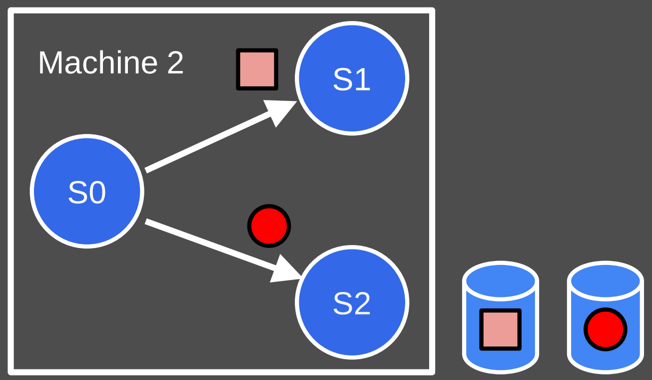


Upsizing = Steps in Reverse



Granularity of Parallelism

As of March 2016, Google Cloud Dataflow:

- Splits Key Ranges initially Based on Max Machines
- At Max: 1 Logical Persistent Disk per Machine
  Each disk has slice of key ranges from all stages
- Only (relatively) even Disk Distributions
- Results in Scaling Quanta

Example Scaling Quanta:
Max = 60 Machines

Parallelism	Disk per Machine
3	N/A
4	15
5	12
6	10
7	8, 9
8	7, 8
9	6, 7
10	6
12	5
15	4
20	3
30	2
60	1

Policy: making Decisions

Goals:

1. No backlog growth
2. Short backlog time
3. Reasonable CPU utilization

Preconditions for Downscaling

Low backlog time

No backlog growth

Low CPU utilization

Downscaling Policy

Next lower scaling quanta => M' machines

Estimate future $CPU_{M'}$ per machine:

$$CPU_{M'} = \frac{M}{M'} CPU_M$$

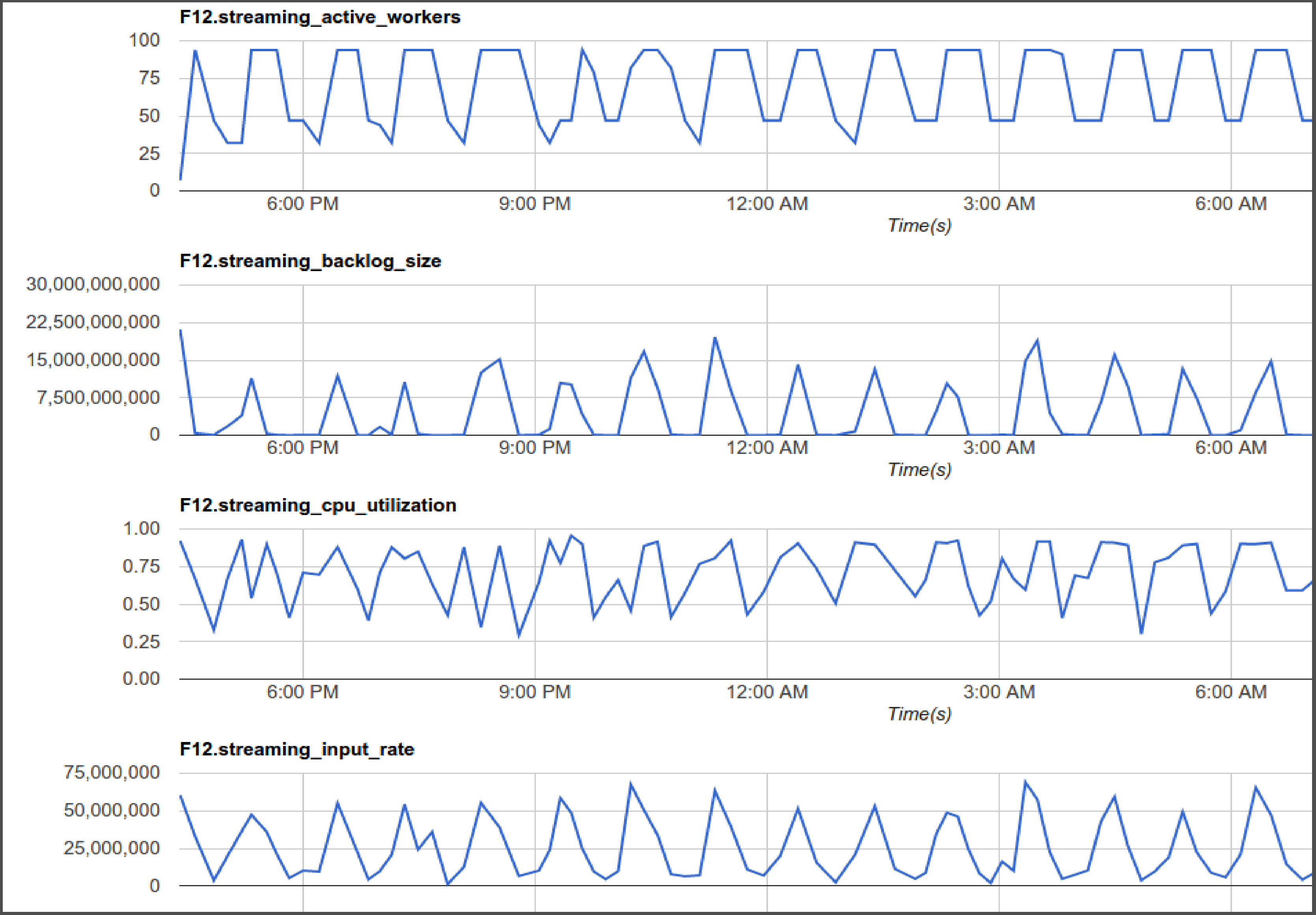
If new $CPU_{M'}$ < threshold (say 90%),

downscale to M'

4

Summary + Future Work

Artificial Experiment



Auto-Scaling Summary

Signals: throughput, backlog time, backlog growth, CPU utilization

Policy: keep up, reduce backlog, use CPUs

Mechanism: split key ranges, migrate computations

Future Work

- Experiment with non-uniform disk distributions to address hot ranges

- Dynamically splitting ranges finer than initially done.

- Approximate model of #VM - throughput relation

Questions?

Further reading on streaming model:

[The world beyond batch: Streaming 101]

[The world beyond batch: Streaming 102]