

Runner Architecture, Management & Autotuning

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The Beam Vision

Provide a comprehensive portability framework for data processing pipelines, one that allows you to write your pipeline once in the programming language of choice and run it with minimal effort on the execution engine of choice



Java

Input.apply
(Sum.integersPerKey())

Python

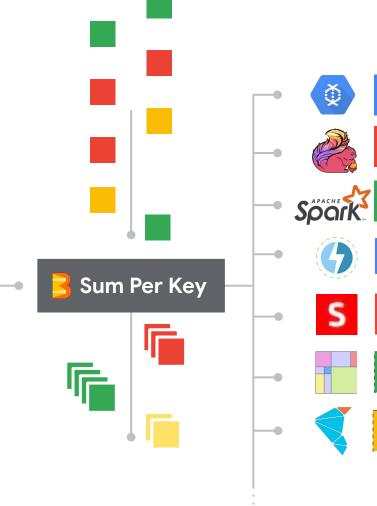
input | Sum.PerKey()

Go

stats.Sum(s, input)

SQL

SELECT key, SUM(value)
FROM input GROUP BY key



Cloud Dataflow

Apache Flink

Apache Spark

IBM Streams

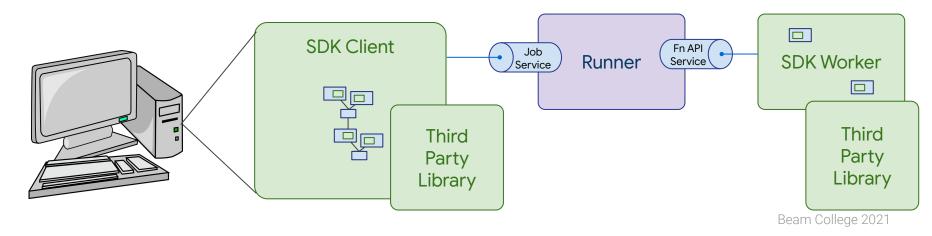
Apache Samza

Apache Nemo (incubating)

Twister2

A choice of language: the SDK

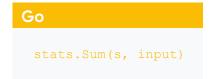
- An SDK is the tool/library that lets the user author Beam pipelines...
- ...and **submit** it to a **runner**...
- ...with support for executing user code in an appropriate environment.



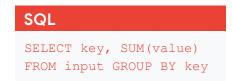
A choice of language: the SDK

- An SDK must be written for each supported language.
 - Provides Beam Model Concepts in a language specific way.



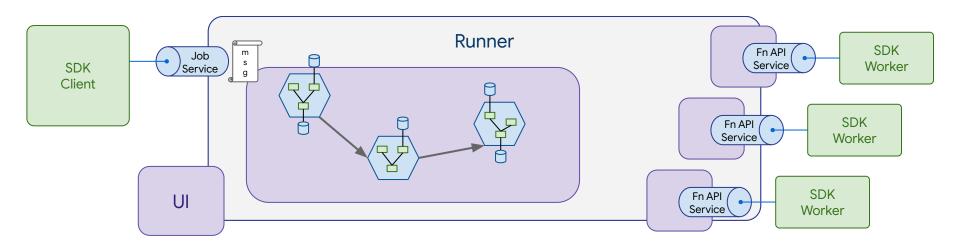




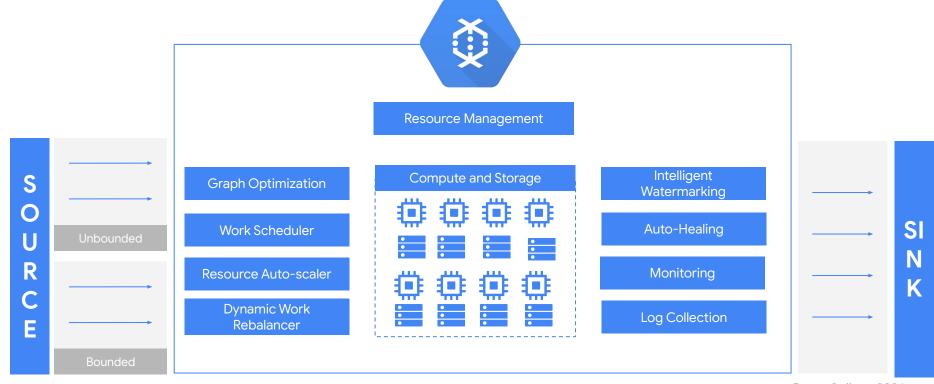


A choice of execution engine: the Runner

- A Runner orchestrates the execution of a pipeline...
- ...in a **distributed*** manner...
- ...while reporting status and results to the user.

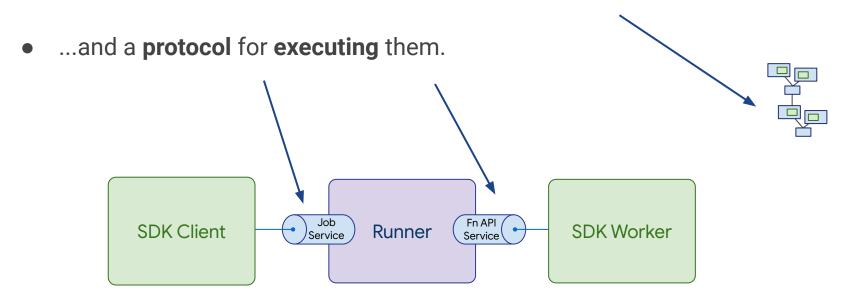


The Google Cloud Platform Runner: Dataflow



The Comprehensive Portability Framework

• A language agnostic way of representing Beam Pipelines...



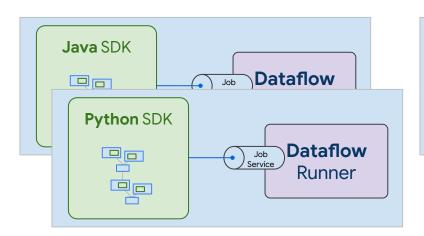
So, what's in it for me?

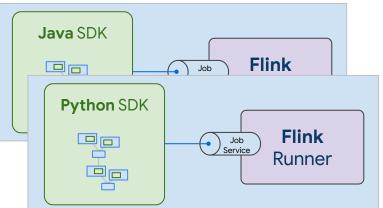
- Every runner works with every language
- Configurable, Hermetic Worker Environment
- Multi-Language Pipelines
- Faster/exclusive delivery of new features, such as Splittable DoFn (SDF)

Without Portability

The state of the s

- Pipelines have to be written in a single language specific SDK
- SDK-runner combinations require **non-trivial work** on both sides





Hermetic Worker Environment

- Code deployed and executed on remote machines
 - Configuration is runner-specific, runner-constrained
- Shipping dependencies is hard
 - Especially in languages without fat jars
- Develop, test locally
 - Often very different than deployment environment



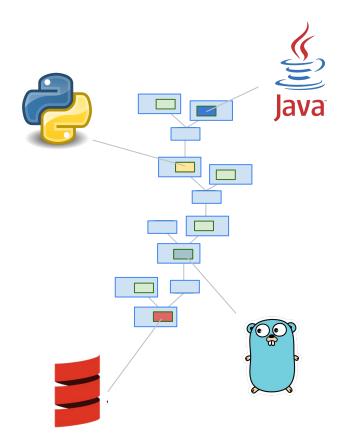




Beam Environments

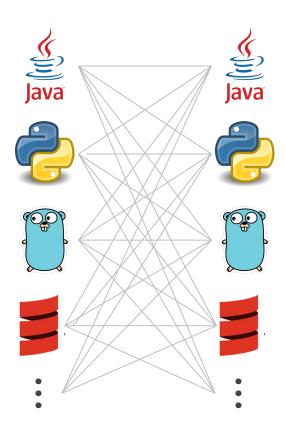
- Each user operation has an associated environment in which to execute.
 - Typically the SDK provides a default environment
- This environment can be specified as an arbitrary Docker container
 - Ahead-of-time installation
 - Arbitrary dependencies
 - Arbitrary customization
 - Runner isolation
- Existing runtime injection of artifacts still supported
 - Jars, packages, binaries
 - Environments can be shared
 - No need to rebuild image on each compile





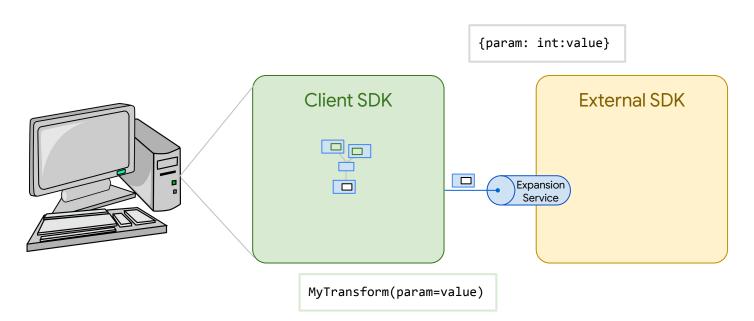
Portability gives us

- Language agnostic representation of pipelines
 - o Transforms, coders, ...
- Per-operation specification of environment
- We are no longer bound to a single SDK in a given pipeline

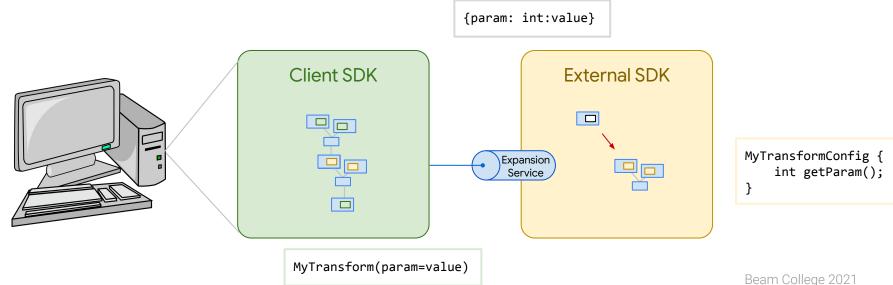


- Transforms can be shared among SDKs
- Rich set of IOs from Java available everywhere
- Tensorflow TFX transforms in non-Python jobs
- Leverage SQL work in Python and Go
- Bootstrap SDKs in other languages
- More libraries available in language of your choice.

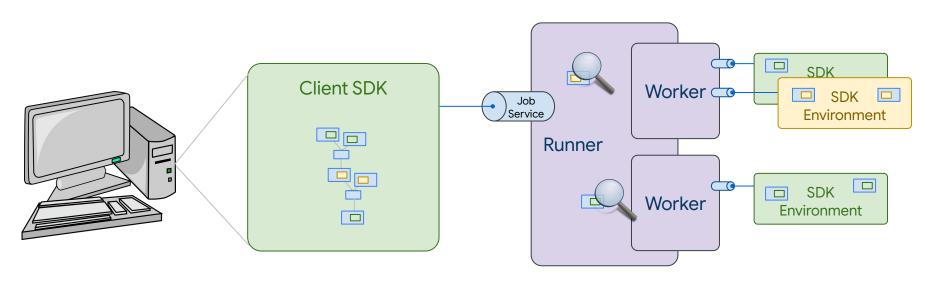
- 1 User constructs pipeline using **SDK-native** conventions
- 2 An **ExternalTransform** is applied
- 3 The transform identifier, with its parameters is sent to an **ExpansionService**



- 4 The transform is **expanded** in the external SDK.
- 5 The expansion is **returned** to the client SDK and **plugged** into the graph.
- 6 Construction continues as before.



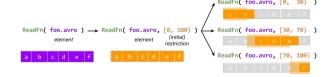
• **Execution** happens by interacting with **multiple environments**.



New Features

Some new features exclusively available via Portability

- SplittableDoFn
 - Radically Modular IO Connectors
- Beam Metrics
 - System metrics, richer user counter types
- New runners and SDKs
 - o E.g. GoLang, Samza runner
- Interactive, Visualization tools





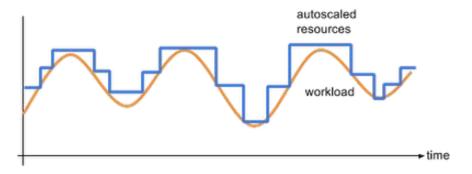




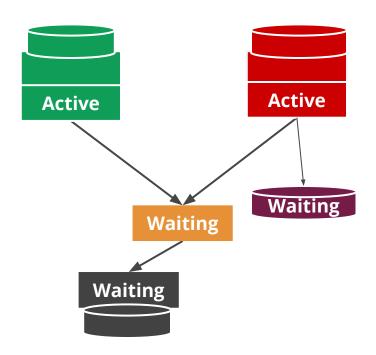


Autoscaling Mechanics (Google Cloud Dataflow)

Batch Work items

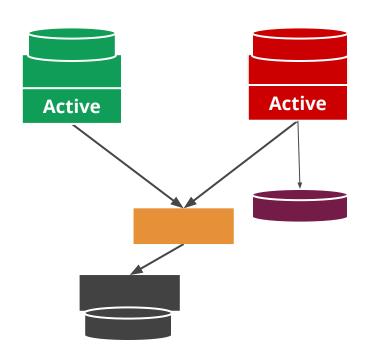


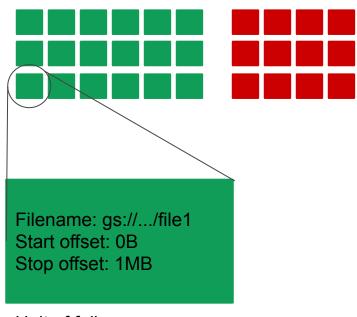
Execution: Batch stages run sequentially



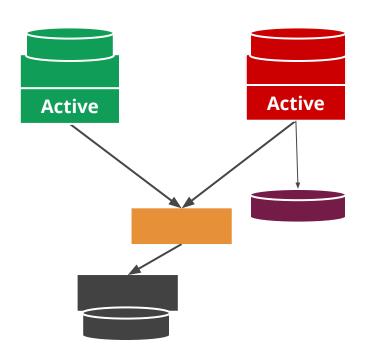
Stages wait for their complete input to be ready.

Execution: Generate Work Items (initial splitting)

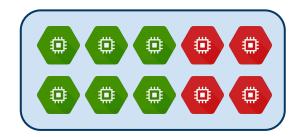




Workers Claim Work Items

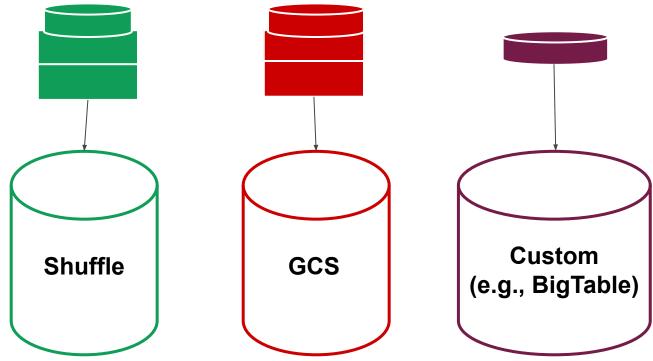




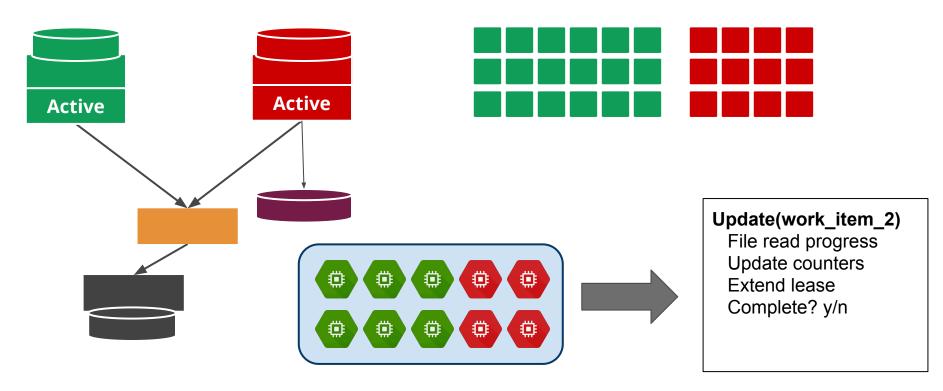


Output Written to Persistent Storage

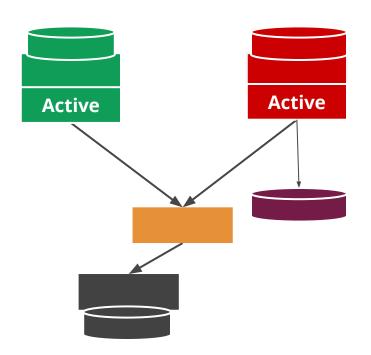
Every completed work item is checkpointed



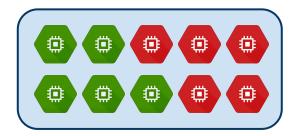
Workers Update Work Item Progress



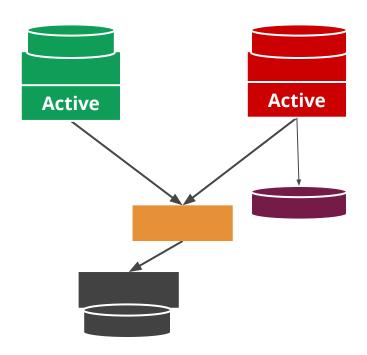
Two stages share the same pool

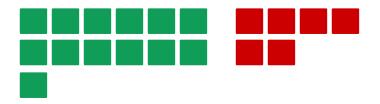


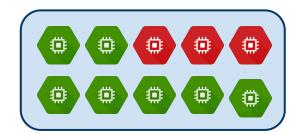




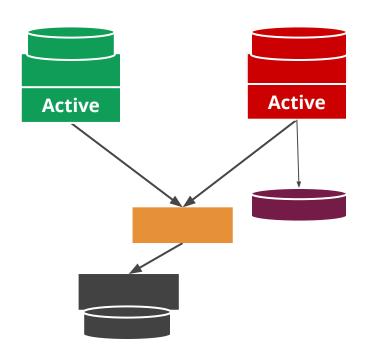
Making steady progress







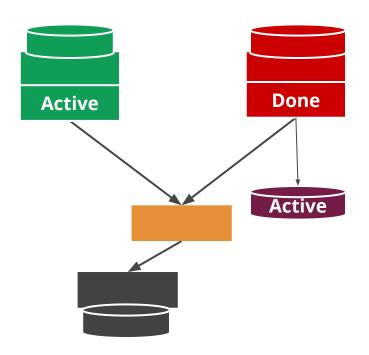
Red stage almost done







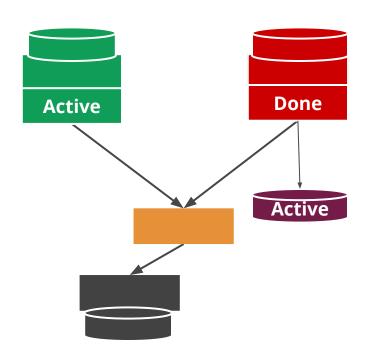
Red stage done, green running, purple unblocked

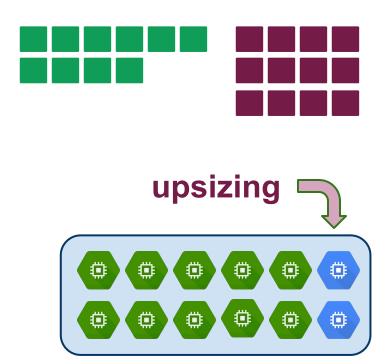




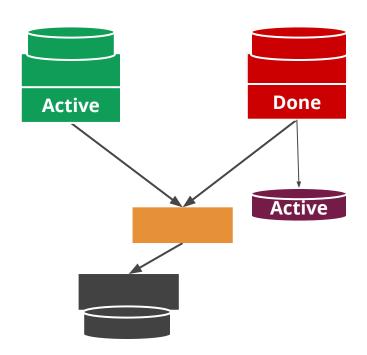


Autoscaling: Add more workers





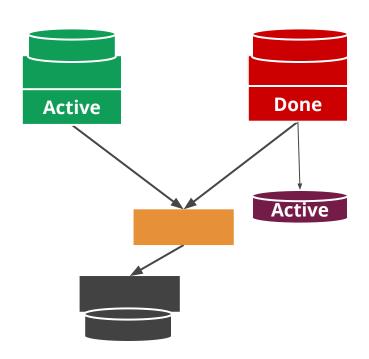
Autoscaling







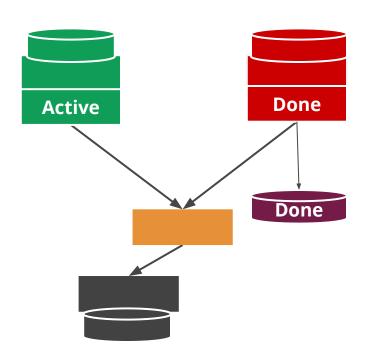
Autoscaling: Purple stage finishing quickly



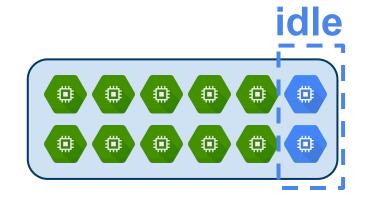




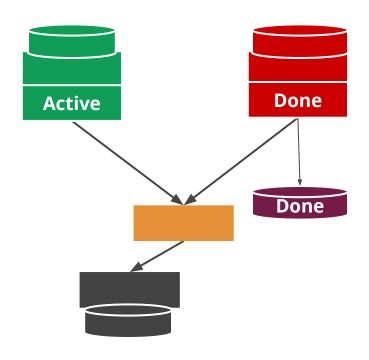
Autoscaling: Purple done, green still active

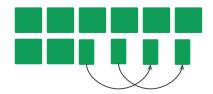






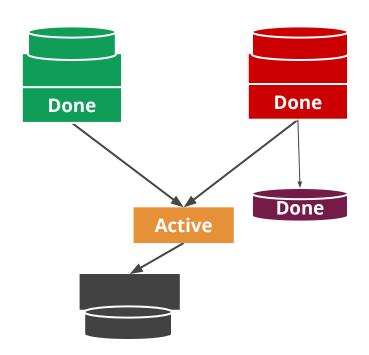
Dynamic Work Rebalancing: Splitting Work





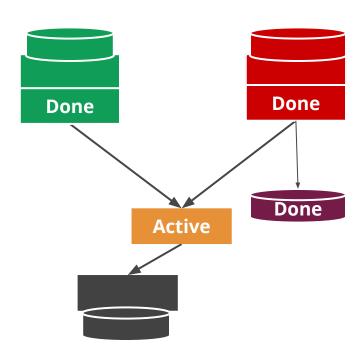


Next Stage: Limited Parallelism





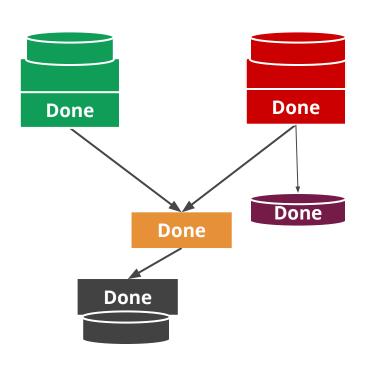
Downscaling







And, finally



Pipeline shuts down

All resources released

All output and counters are available

Pipeline is marked as done in the UI and API

Summary

- 1. Beam vision
- 2. Basics of the SDK
- 3. Basics of Runners
- 4. Portability framework & its advantages
- 5. Autoscaling (Dataflow specific)

Thank you!

Questions?

