Koji: Automating pipelines with mixed-semantics data sources

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ABSTRACT

We propose a new result-oriented semantic for defining data processing workflows that manipulate data in different semantic forms (files or services) in a unified manner. This approach enables users to define workflows for a vast variety of reproducible data-processing tasks in a simple declarative manner which focuses on application-level results, while automating all control-plane considerations (like failure recovery without loss of progress and computation reuse) behind the scenes.

The uniform treatment of files and services as data enables easy integration with existing data sources (e.g. data acquisition APIs) and sinks of data (e.g. database services). Whereas the focus on containers as transformations enables reuse of existing data-processing systems.

We describe a declarative configuration mechanism, which can be viewed as an intermediate representation (IR) of reproducible data processing pipelines in the same spirit as, for instance, TensorFlow [12] and ONNX [16] utilize IRs for defining tensor-processing pipelines.

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1 INTRODUCTION

1.1 History

The introduction of MapReduce [4] by Google arguably marked the beginning of programmable large-scale data processing. MapReduce performs a transformation of one set of large files (the input) into another (the output). Since the transformation provided by a MapReduce is a primitive fit? a many-to-many shuffle, followed by an element-wise map fit? it became common practice to chain multiple MapReduce transformations in a pipeline.

The dataflow in such a pipeline is cleanly captured by a directed-acyclic graph (DAG), whose vertices represent transformations and edges represent files.

In a twist, it became commonplace to query a service (usually a key-value lookup service) from inside the mapper function. For instance, this technique is used to join two tables by mapping over one of them and looking up into the other. More recently, Machine Learning systems have been serving trained models as lookup services, which are used by MapReduce mappers in a similar fashion.

With this twist, a MapReduce transformation no longer depends just on input files but also on lookup services (and their transitive dependencies, which are usually other files). The simple dataflow model mentioned previously no longer applies.

To the best of our knowledge, no dataflow model has been proposed to capture this scenario. Yet, to this day, this type of mixed-semantic (file and service) pipelines represent the most common type of off-line batch-processing workflows.

Due to the lack of a specialized formalism for describing them and a tool for executing them, they are currently codified in a variety of error-prone ways, which usually amount to the usage of data-unaware task execution pipelines. We address this gap here.

1.2 Problem

We address a class of modern Machine Learning and data-processing pipelines.

Such pipelines transform a set of input files through chains of transformations, provided by open-source software (OSS) for large-scale computation (like TensorFlow [12], Apache Beam [6], Apache Spark [8], etc.) or user-specific implementations (usually provided as executable containers). In short, these pipelines use mixtures of disparate OSS technologies tied into a single coherent data flow.

At present, such workflows are frequently built using task-driven pipeline technologies (like Apache Airflow [5]) which execute tasks in a given dependency order, but are unaware of the data passed from one task to the next. The lack of data flow awareness of current solutions prevents large data-processing pipelines from benefiting in caching and reuse of computation, which could provide significant efficiency gains in these industry cases:

- Restarting long-running pipelines after failure and continuing from where previous executions left off.
- Re-running pipelines with incremental changes, during developer iterations.
- Running concurrent pipelines which share logic, i.e. compute identical data artifacts within their workflow.

Furthermore, task-centric technologies make it impractically hard to integrate data and computation optimizations like:

- In-memory storage of intermediate results which are not cache-able, or
- Context-specific choices of job scheduling and placement algorithms.

1.3 Solution

We propose a new pipeline semantic (and describe its system architecture, which can be realized on top of Kubernetes) based on a few key design choices:

- Result-oriented specification: The goal of workflows is to build data artifacts. Workflows are represented as dependency graphs over artifacts. Input artifacts are provided by the caller. Intermediate artifacts are produced through a computation, using prior artifacts. Output artifacts are
We aim for this to be a pipeline technology which can perform data transformations based on any software available, as OSS-for-Linux or as-a-Service. This goal informs our choice of Kubernetes, as an underlying infrastructure and cluster management technology for coordinating orchestration of backend execution runtimes on single or multi-tenant physical or (multi)cloud computing resources.

Kubernetes [13], which is becoming the industry-standard cluster OS, is ubiquitously available on most cloud providers, can be run on-premises, and is generally provider-agnostic from the users’ standpoint. Kubernetes benefits from having mature integrations to the Docker (and other) container ecosystems, providing seamless out-of-box access to many data tools, thanks to the rich ecosystem of operator implementations [14].

1.4 How it works

The user defines a pipeline in a language-agnostic manner. A pipeline definition describes: (i) input data resources and their sources, (ii) intermediate resources and the data transformation that produced them from dependent resources, (iii) output data resources and where they should be delivered.

- Resources are files (or services) and their format (or protocol) can be optionally specified to benefit from type-safety checks over the dataflow graph, thanks to declarations.
- Input resources can be provided by various standard methods (volume files, existing cluster services, Amazon S3 buckets, and so on.). Data source types can be added seamlessly.
- Intermediate resources are described as files (or services), optionally with a specified format (or protocol). Their placement location is not provided by the user, in order to enable the pipeline controller to make optimal choices in this regard and to manage caching placements decisions.
- Output resources can specify the location where they should be delivered, with standard (and extensible) options similarly to the case for input resources.

The transformations at the nodes of the dataflow graph consume a set of input resources to produce new resources. Transformations are exposed to the user with a clean application-level interface. A transformation:

- Consumes a set of named input resources (the arguments), which can be fulfilled by prior resources in the user’s dataflow program.
- Produces a set of named output resources. The latter can be referenced (by name) by dependent transformations, downstream in the dataflow program.
- Accepts a transformation-specific set of parameters. For instance, a TensorFlow transformation may require a TensorFlow program (e.g. as a Python or Protocol Buffer file).

The user programs (in Python or Go) which build the pipeline dataflow are used to generate a Protocol Buffer (or YAML) file, which captures the entire pipeline and is effectively executable and reproducible.

Pipelines can be executed either from the command-line or by sending them off as a background job to Kubernetes, using the operator pattern (via CRD).

2 AN EXAMPLE

A typical modern Machine Learning pipeline produces interdependent files (e.g. data tables) and services (e.g. trained model servers) at multiple stages of its workflow.

The following example captures all semantic aspects of a modern ML/ETL pipeline:

- **Unified treatment of data and services**: We view file artifacts and service artifacts in a unified way as resources. This allows us to describe complex workflows which mix-and-match batch and streaming computations (the latter being a special case of services). Furthermore, this enables us to automate service garbage-collection and achieve optimal computation reuse (via caching) across the entire pipeline. The resource-level unified view of files and services purports to be the Goldilocks level of coarse data knowledge, that is needed by a dataflow controller to automate all file caching and service control considerations.

- **Type-safe declarative specification**: We believe that workflow specification has to be declarative, i.e. representable via a typed schema (like e.g. Protocol Buffers). This provides full decoupling from implementations, and serves as a reproducible assembly language for defining pipelines.

- **Decouple dataflow from transform implementation**: We decouple the specification of application logic from the definition of how data transforms are performed by underlying backend technologies. Application logic comprises the dependency graph between artifacts, and the data transform at each node. Data transforms are viewed uniformly akin to functions from a library of choices. The methods for invoking transformation-backing technologies (like MapReduce, TensorFlow, etc.) are implemented separately as driver functions, and surfaced as a library of declarative structures that can be used in application logic.

- **Extensible transformations**: New types of data transforms (other than container-execution based) can be added easily. This is done in two parts. First, a simple driver function implements the specifics of calling the underlying technology. Second, a new transformation structure is added to the application logic schema. This extension mechanism is reserved for transformations that cannot be containerized.

- **Scheduler and storage-independent design**: Application logic governs the order in which data computations must occur. However, The choice of job schedulers (or placement) algorithms, as well as the choice of storage technologies (e.g. disk versus memory volumes), are entirely orthogonal to the application’s dataflow definition. Our architecture enables flexible choice of relevant technology on a per-node (scheduling) and per-edge (storage) basis. For instance, some intermediate files can be stored in memory volumes, instead of disk, to increase efficiency.

The following example captures all semantic aspects of a modern ML/ETL pipeline:
Figure 1: An example workflow which uses different technologies. Solid edges represent file resources. The dashed edge represents a service resource.

- **INPUTS**: The pipeline expects two input resources from its caller: a training table, called TRAIN, and a table of business data, called BUSINESS.
- **STEP 1**: Table TRAIN is used as input to a Machine Learning procedure, e.g. TensorFlow training, to produce a new table, we call MODEL. This is a batch job: It processes an input file into an output file.
- **STEP 2**: Table MODEL is then used as input to bring up a Machine Model Server, e.g. TensorFlow Serve. The server loads the trained model in memory, and starts a model-serving API service at a network location, we call SERVICE.
- **STEP 3**: Table BUSINESS together with service SERVICE are used as input to an application-specific MapReduce job, which annotates every record in BUSINESS with some insight from SERVICE and outputs the result as table INSIGHT.
- **OUTPUT**: Table INSIGHT is the result of the pipeline.

A few things are notable here:

(N1) The pipelines inputs, intermediate results and outputs are either files or services, which we call collectively resources

(N2) The pipeline program describes a dependency graph between the resources: MODEL depends on TRAIN, SERVICE depends on MODEL, and INSIGHT depends on BUSINESS and MODEL.

(N3) The outputs of pipeline steps (be it content of files produced, or behavior of services rendered) depend deterministically on their inputs.

To summarize, this view of a data-processing pipeline captures resource dependencies and resource semantics (files or services), while treating computations as black-box deterministic procedures (provided by containers, in practice).

This coarse container/resource-level view of a pipeline suffices to automate pipeline execution optimally and achieve significant compute and space efficiencies in common day-to-day operations.

Let us illustrate this with two examples:

- **Example 1**: Suppose, after execution, the pipeline completes steps 1 and 2, then fails during step 3 due to hardware dysfunction.
  
  Due to the determinism (N3) of pipeline steps, it is possible to cache the file results of intermediate computations, in this case table MODEL, so they can be reused.
  
  When the pipeline is restarted after its failure, the caching mechanism would enable it to skip step 1 (a costly training computation) and proceed directly to restarting the service in step 2 (which takes negligible time) and then renewing the interrupted computations in step 3.

- **Example 2**: In another example, suppose the pipeline is executed successfully with inputs BUSINESS1 and TRAIN. On the next day, the user executes the same pipeline with inputs BUSINESS2 and TRAIN, due to updates in the business table.
  
  The change in the BUSINESS table does not affect the computations in step 1 and 2 of the pipeline. Therefore just as in the previous example, an optimal pipeline would skip these steps and proceed to step 3.

3 RELATED WORK: PIPELINE TAXONOMY

Here we position the pipeline technology proposed in this paper against related technologies in the OSS ecosystem.

For the sake of our comparison, we identify two types of pipeline/workflow technologies: task-driven and data-driven. Additionally, data-driven pipelines are subdivided into coarse-grain and fine-grain types.

Task-driven pipeline technologies target the execution of a set of user tasks, each provided by an executable technology (e.g. binary or container), according to a dependency graph order. A task executes only after its dependencies have finished successfully. Task-driven pipelines provide simple (usually per-task) facilities for recovering from failure conditions, like restart rules. In general, task-driven pipelines are not aware of the flow of data (or services) provided by earlier tasks to later ones.

Data-driven pipeline technologies aim to define and perform reproducible transformations of a set of input data. The input is usually consumed either from structured files (representing things like tables or graphs, e.g.) located on a cluster file-system, or databases available as services. The outputs are produced in a similar fashion. Data transformations are specified in the form of a directed acyclic dataflow graph, comprising data transformations at the vertices.
4 SEMANTICS

In this section, we discuss the proposed semantics.

4.1 Representation

4.1.1 Dataflow topology. A data-processing pipeline is represented as a directed acyclic graph, whose vertices and edges are called steps and dependencies, respectively.

- Every pipeline vertex (i.e. step) has an associated set of named input slots and a set of named output slots.
- Every directed pipeline edge (a dependency) is associated with (1) an output slot at its source vertex, and (2) an input slot at its sink vertex.

Output slots can have multiple outbound edges, reflecting that the output of a step can be used by multiple dependent steps. Input slots, on the other hand, must have a unique inbound edge, reflecting that a step input argument is fulfilled by a single upstream source.

4.1.2 Steps and transformations. In addition to their graph structure, steps and dependencies are associated with computational meaning.

Each dependency (i.e. directed graph edge) is associated with a resource, which is provided by the source step and consumed by the sink step (of the dependency edge).

Resources are analogous to types in programming languages: They provide a ficompile-time description of the data processed by the pipeline at execution time.

Pipeline resource descriptions capture both the data semantics (file or service) as well as the data syntax (file format or service protocol).

Each step (i.e. graph vertex) is associated with a (description of a) transform. A transform is a computational procedure which, at execution time, consumes a set of input resource instances and produces a set of output resource instances, whose names and resource types are as indicated by the inbound and outbound edges of the pipeline step.
There are two distinguished transform (i.e. vertex) types, called *argument* and *return* transforms, which are used to designate the inputs and outputs of the pipeline itself. Argument transforms have no input dependencies and a single output dependency. Return transforms have a single input dependency and no output dependencies.

Steps which are not based on argument or return transforms are called *intermediate*.

### 4.2 Execution model

When a pipeline is executed by a *caller* (either a human operator or through programmatic control), a pipeline controller is allocated to dynamically manage the execution of the pipeline towards the goal of delivering the pipeline’s return resources to the caller.

The key technical challenge in designing the pipeline control logic is to devise a generic algorithm which is robust against process failures, while also accommodating for the semantic differences between file and service resources:

- File resources are considered available after the successful termination of the transformation process that produces them,
- Service resources are considered available during the execution of the transformation process that produces them.

#### 4.2.1 Control algorithm

The pipeline execution algorithm, performed by the *pipeline controller*, associates two state variables with each dependency (edge) in the pipeline graph:

- A variable that assumes one of the states *fiavailable* or *finot available*, indicates whether the underlying resource (file or service) is currently available. This variable is written by the supervisor of the step producing the dependency, and read by the supervisor of the step consuming the dependency.
- A variable that assumes one of the states *fineeded* or *finon needed*, indicating whether the underlying resource (file or service) is currently needed. This variable is written by the supervisor of the step consuming the dependency, and read by the supervisor of the step producing the dependency.

On execution, the pipeline controller proceeds as follows:

1. Mark the state of each input dependency to a return step as *fineeded*. These dependencies will remain *fineeded* until the pipeline is terminated by the caller.
2. For each intermediate step in the pipeline graph, create a step *supervisor*, running in a dedicated process (or co-routine).

Every step supervisor comprises two independent sub-processes: a *driver loop* and a *process collector loop*.

The driver loop is responsible for *fsensing* when the outputs of the supervised step are needed dynamically (by dependent steps) and arranging for making them available.

1. Repeat:
   - If the step has no output dependencies which are *fineeded* and *finot available*, then goto (1).
   - Otherwise:

The (process) collector loop is responsible for sensing when the outputs of the supervised step (there is a collector for each step in the pipeline) are not needed any longer and arranging to garbage-collect its process.

1. Repeat:
   - If the step process is running and all of the following conditions hold, then kill the process:
     - All file output dependencies of the step are either *fineeded* and *fiavailable* or *finot needed*.
     - All service output dependencies of the step are *finot needed*.
   - Goto (1).

#### 4.3 Pure functions and causal hashing of content

Most data-processing pipelines in industry are required, by design, to have reproducible and deterministic outcomes. This includes workflows such as Machine Learning, banking and finance, canarying, software build systems, continuous delivery and integration, and so on.

In all reproducible pipelines, by definition, step transformations are *pure*: The outcomes (files output or services provided) obtained from executing pure transformations are entirely determined by the inputs provided to them and the identity (i.e. program description) of the transformation.

By contrast, non-reproducible pipelines are ones where transformation outcomes might additionally be affected by:

- runtime information (like the value of the wall clock or the temperature of the CPU), or


- interactions with an external stateful entity (like disk, a persistent store service, or outside Internet services, for instance).

4.3.1 Caching. In the case of reproducible pipelines (comprising pure transformations), pipeline execution can benefit from dramatic efficiency gains (in computation, communication and space), using a simple technique we call causal caching.

The results of pipeline steps which are based on purely deterministic transformations can be cached to obtain significant efficiency gains in the following situations:

1. Avoiding duplicate computations when restarting partially-executed pipelines, for instance, after a hardware failure;
2. Multiple executions of the same pipeline, perhaps by different users concurrently or at different times;
3. Executions of pipelines that have similar structure, for instance, as is the case with re-evaluating the results of multiple incremental changes of the same base pipeline during development iterations.

The caching algorithm assigns a number, called a causal hash, to every edge of the computation graph of a pipeline. These hash numbers are used as keys in a cluster-wide caching file system.

To serve their purpose of cache keys for the outputs of pipeline steps, causal hashes have to meet two criteria:

1. A causal hash has to have the properties of a content hash: If the causal hashes of two resources are identical, then the resources must be identical.
2. A causal hash has to be computable before the resource it describes has been computed, by executing the step transformation that produces it.

To meet these criteria, we define causal hashes in the following manner:

1. The causal hashes of the resources passed as inputs to the pipeline are to be provided by the caller of the pipeline. Criteria (C2) does not apply to input resource, thus any choice of a content hashing algorithm, like using an MD5 message digest or a semantic hash, suffices.
2. All other pipeline edges correspond to resources output by a transformation step. In this case, the causal hash of the resource is defined recursively, as the message digest (e.g. using SHA-1) of the following meta information:
   a. The pairs of name and causal hash for all inputs to the step transformation,
   b. The identity (or program description) of the transformation,
   c. The name of the transformation output associated with the edge.

Note that while only file resources can be cached (on a cluster file system), service resources can also benefit from caching. For instance, a service resource in the middle of a large pipeline, can be made available if the file resources it depends on have been cached from a prior execution.

4.3.2 Locking and synchronization. Pipeline semantics make it possible to execute multiple racing pipelines in the same cluster, while ensuring they utilize computational resource optimally.

Two different pipeline graphs can entail similar transformations in the sense of a common computational subgraph, appearing in both pipelines.

This situation occurs, for instance, as a developer iterates over pipeline designs incrementally, producing many similar designs.

A causal cache (as described earlier) shared between concurrent pipelines enables one pipeline to reuse the computed output of an identical step, that was already computed by the other pipeline.

We accomplish cache sharing across any number of concurrently executing pipelines by means of per-causal-hash cluster-wide locking.

In particular, the controller algorithm for executing a pipeline transformation step is augmented as follows:

1. Compute the causal hashes, H, of the step outputs
2. Obtain a cluster-wide lock on H
3. Check if the output resources (files) have already been cached in a designated caching file system:
   (a) If so, then release the lock on H and reuse the cached resources.
   (b) Otherwise, execute the step transformation, cache its outputs, release the lock on H and return the output resources.

4.3.3 Composability. The reader will note that a pipeline can be viewed as a transform: It has a set of named inputs (the arguments), a set of named outputs (the return values) and a description of an executable procedure (the graph).

Consequently, one pipeline can be invoked as a step transformation in another.

This generic and modular flexibility enables developers to create pipeline templates for common workflows, like a canary-ing workflow or an ML topology, and reuse those templates as building blocks in multiple applications.

5 ARCHITECTURE

Our goal here is to describe an architecture for a data-processing pipeline system, and outline an implementation strategy that works well with available OSS software.

We focus on an approach that uses Kubernetes as underlying infrastructure, due to its ubiquitous deployments in commercial clouds.

The pipeline execution logic itself is implemented as a Go library, which can execute a pipeline given runtime access to a Kubernetes cluster and a user pipeline specification. Pipeline executions can be invoked through standard integration points: (a) using a command-line tool by passing a pipeline description file, (b) using a Kubernetes controller (via CRD), or (c) from any programming language by sending pipeline configurations for execution to the controller interface in (b).

The approach (c) is sometimes called configuration-as-code and is a common practice. For instance, TensorFlow and PyTorch are Python front-ends for expressing tensor pipelines. Using general imperative languages to express pipelines has proven suboptimal for various reasons. For one, pipelines (in the sense of DAG data flows) correspond to immutable functional semantics (not imperative mutable ones). Furthermore, configuration-as-code libraries have not been able to deliver type-safety at compile-time. To solve for both...
of these problems, we have designed a general functional language, called Ko [1], which allows for concise type-safe functional-style expression of pipelines.

5.1 Type checks before execution
The pipeline specification schema allows the user to optionally specify more detailed file information about the resources input to or output by each transformation in a dataflow program.

For file resources, this type information can describe the underlying file and its data at various levels of precision. It could specify a file format (e.g. CSV or JSON), an encoding (e.g. UTF8) and a data schema (e.g. provided as a reference to a Protocol Buffer or XML schema definition).

For service resources, analogously, the user can optionally describe the service type in to a varying level of detail: transport layer (e.g. HTTP over TCP), security layer (e.g. TLS), RPC semantics (e.g. GRPC), and protocol definition (e.g. a reference to a Protocol Buffer or an OpenAPI specification).

When such typing information is provided, the pipeline controller is able to check the user’s dataflow programs for type-safety, before it commits to a lengthy execution, as is often the case.

5.2 Resource management and plumbing
At the programming level, the user directly connects the outputs of one transformation to the inputs of another.

At runtime, however, these intermediate resources file? be it files or services file? need to managed.

5.2.1 Files. For intermediate file resources, generally, the pipeline controller will determine the placement of files on a cluster volume and will connect these volumes as necessary to containers requiring access to the files.

For instance, assume transformation A has an output that is connected to an input of transformation B. At runtime, the controller will choose a volume for placing the file produced by A and consumed by B. It will attach this volume to the container for A during its execution, and then it will attach the volume (now containing the produced file) to the container for B. Plumbing details such as passing execution flags to containers are handled as well.

Of course, this is a basic example. The file management logic can be extended with hooks to fulfill various optimization and policy needs, such as:

- Plugging third-party file placement algorithms that optimize physical placement locality, or
- Placing non-cacheable resources on memory-backed volumes,

The file management layer also contains the causal-hash-based caching of files (described in the previous section).

5.2.2 Services. For intermediate services resources file? provided from one transformation to the next file? the pipeline controller handles plumbing details transparently, as well. Generally, it takes care of creating DNS records for services, and coordinating container server addresses and flag-passing details.

As with files, services between a server and a client transformation, can be customized via hooks to address load-balancing, re-routing, authentication, and other such concerns.

5.3 Transformation backends
A transformation is, generally, any process execution within the cluster, which accepts files or services as inputs, and produces files or provides services as output.

From a technology point of view, a transform can be:

1. The execution of a container,
2. The execution of a custom controller, known as a Kubernetes CRD. For instance, the kubeflow controller is used to start TensorFlow jobs against a running TensorFlow cluster (within Kubernetes),
3. More generally, the execution of any programming code that orchestrates the processing of input resources into output resources.

To accommodate such varying needs, Koji provides a simple mechanism for defining new types of transforms as needed.

From a system architecture perspective, a transform comprises two parts:

1. A schema for the declarative configuration that the user provides to instantiate transforms of this type, and
2. A backend implementation which performs the execution, given a configuration structure (and access to the pipeline and cluster APIs).

Optionally, such backends can install dependent technologies during an initialization phase. For instance, a backend for executing Apache Spark jobs might opt to include an installation procedure for Apache Spark, if it is not present on the cluster.

This paper uses container execution as the running example throughout the sections on semantics and specification. In practice, most legacy/existing OSS technologies will require a dedicated backend, due the large variety of execution and installation semantics.

Fortunately, writing such backends is a short one-time effort. One can envision amassing a collection of backends for common technologies like Apache Spark, Apache Beam, TensorFlow, R, and so on.

Each such technology will define a dedicated configuration structure, akin to Container (in the specification section), which captures the parameters needed to perform a transform execution. We believe that such a simple-to-use declarative library of transforms backed by OSS technologies provides standardized assembly-level blocks for expressing business flows, in general.

5.4 Transform job scheduling
The pipeline controller orchestrates the execution of transforms in their dependency order: A transformation step is ready to execute only when the resources it depends on become available.

Beyond this semantic constraint on execution order, transform jobs can be scheduled to meet additional optimization criteria like throttling or locality of placement.

Optimized job scheduling (and placement) is generally provided by various out-of-the-box products, like Medea [10], for instance.

Since job scheduling considerations are orthogonal to the pipeline execution order, our architecture makes it easy to plug in any scheduling algorithm available out-of-the-box.
This is accomplished by implementing a short function which the pipeline controller uses to communicate with the scheduler when needed. Transform steps can be annotated (in the pipeline’s declarative configuration) with tags that determine their scheduling affinities which would be communicated to the scheduler.

5.5 Recursion

Pipelines can be executed from multiple places in the software stack, e.g.

1. Using a command-line tool, which consumes a pipeline configuration file (YAML or Protocol Buffers),
2. Using a Kubernetes CRD whose configuration schema understands the pipeline schema shown here,
3. From any program running in the cluster, using a client library, also by providing a pipeline configuration as an execution argument.

In particular, for instance as implied by the last method, a program that runs as a transform in one pipeline can fi? as part of its internal logic fi? execute another pipeline.

In the presence of such recursive pipeline invocation, all data consistency and caching guarantees remain in effect, due to the powerful nature of causal hashes. This enables developers to build complex recursive pipelines, such as those required by Deep Learning and Reinforcement Learning methodologies.

Due to the ability to execute pipelines recursively and the modular declarative approach to defining pipelines as configurations, our pipeline system can directly be reused as the backend of a DSL for programming data-processing logic at the cluster-level.

We have made initial strides in this direction with the design and implementation of the Ko programming language. We defer this extension to a follow up paper.

6 CONCLUSION

This paper has two main contributions. First, we make the observation that virtually all large-scale, reproducible data-processing pipelines follow a common pattern, when viewed at the right level of abstraction.

In particular, at a semantic level, said pipelines can be viewed as dependency-based build tools for data, akin to code build tools for software. Within this context, however, pipelines differ from build tools for code in that the resources being depended on can be files as well as short-lived services.

Our second contribution is to cast these two types of resources fi? which have very different runtime semantics fi? into a unified framework, where either can be viewed merely as a simple “resource dependency” from the point of view of the user.

To make this possible, we introduce Causal Hashing which is a method for generating content hashes for both files and services. Causal Hashing is thus a generalization of content hashing, which can assign unique content IDs to complex temporal objects (like services).

Causal Hashing unlocks the complete automation of a myriad of tasks, such as caching, conflict resolution, version tracking, incremental builds and much more.

A SPECIFICATION

A.1 Specification methodology

Programmable technologies, in general, expose the user-programmable functionality in one of two ways. Either by using a (general or domain-specific) programming language, or using a typed declarative schema (captured by standard technologies like XML, YAML, Thrift or Protocol Buffers, for instance) for expressing program configurations.

For instance, Apache Spark and Apache Storm are programmable through Java. Gleam, a MapReduce reduce implementation in Go, is programmable through Go. On the other hand, TensorFlow and Argo express their programs in the form of computational DAGs captured by Protocol Buffers and YAML, respectively.

The use of typed data structures, in the form of Protocol Buffers, for defining programmable software has been a wide-spread practice within Google, for many years now.

This declarative/configuration approach has a few advantages.

The configuration schema for any particular technology acts as an assemblage language for that technology and provides a formal decoupling between programmable semantics and any particular implementation. Furthermore, declarative configurations being data succumb to static analyses (for validity, security or policy, e.g.) prior to execution, which is not the case with DSL-based interfaces.

Configuration schema are language-agnostic, as they can be generated from any general programming language: a practice widely used and known as configuration-as-code.

The declarative schema-based approach is gaining momentum in the OSS space as well, as witnessed for instance by projects like ONNX. ONNX defines a platform-independent programming schema for describing ML models in the form of an extensible Protocol Buffer. ONNX aims to be viewed as a standard, to be implemented by various backends.

In this spirit, we believe that the correct interface for defining a general-purpose data-processing pipeline is the typed declarative one. We use Protocol Buffers as they provide a time-tested extension mechanism for the definition of backward- and forward-compatible data schemas. But it should be understood that interoperability with other standards like OpenAPI and YAML is a given, using standard tooling.

A.2 Pipeline

A pipeline is a directed acyclic graph whose vertices, called pipeline steps, represent data-processing tasks and whose edges represent file or service dependencies between pairs of steps.

At the highest level, a pipeline is captured by message Pipeline, shown below:

```protobuf
message Pipeline {
  repeated Step steps = 1;
}
```

A pipeline is an executable application, which will (1) consume some inputs from its cluster environment (e.g. files and directories from a volume, or a stream of data from a micro-service API), (2) process these inputs through a chain of transformation steps, and (3) deliver some outputs (which could be data or services).
A.3 Steps
A pipeline step is the generic building-block of a pipeline application. Steps are used to describe the inputs, intermediate transformations, and outputs of a pipeline application.

A step is captured by message Step below:

```protobuf
message Step {
  required string label = 1;
  repeated StepInput inputs = 2;
  required Transform transform = 3;
}
```

Each step is identified by a unique string label, which distinguishes it from other steps in the pipeline. This is captured by field label.

The step definition specifies the transformation being performed by the step, as well as the sources for the transformation's inputs relative to the pipeline.

The step's transformation is captured by field transform. Transformations are self-contained descriptions of data processing logic (described in more detail later).

Each transformation declares a list of named and typed inputs (which can be viewed akin to functional arguments), as well as a list of named and typed outputs (which can be viewed akin to functional return values).

Field inputs describes the source of each named input, expected by the step's transformation. Each named input is matched with another step in the pipeline, called a provider, and a specific named output at the provider step.

This matching between inputs and provider steps is captured in message StepInput below:

```protobuf
message StepInput {
  required string name = 1;
  required string provider_step_label = 2;
  required string provider_output_name = 3;
}
```

A.4 Transform
A transform is a self-contained, reusable description of a data-processing computation, based on containerized technology.

Akin to a function (in a programming language), a transform comprises: (1) a set of named and typed inputs, (2) a set of named and typed outputs, and (3) an implementation, which describes how to perform the transform using containers.

Transforms are described by message Transform below:

```protobuf
message Transform {
  repeated TransformInput inputs = 1;
  repeated TransformOutput outputs = 2;
  required TransformLogic logic = 3;
}
```

A.4.1 Transform inputs and outputs. Transform inputs and outputs are captured by messages TransformInput and TransformOutput below.

```protobuf
message TransformInput {
  string name = 1;
  Resource resource = 10;
}
message TransformOutput {
  string name = 1;
  Resource resource = 10;
}
```

The inputs (and outputs) of a transformation are identified by unique names.

These names serve the purpose to decouple the pipeline wiring definitions (captured in messages Step and StepInput) from the implementation detail of how inputs are passed to the container technology backing a transform (captured within message TransformLogic).

Each input (and output) is associated with a resource type, which is captured in field resource.

A.5 Resources
A resource is something that a transform consumes as its input or produces as its output.

The type of a resource is defined using message Resource below. A Resource should have exactly one of its fields, file or service, set.

```protobuf
message Resource {
  optional FileResource file = 1;
  optional ServiceResource service = 2;
}
```

Resource types capture the file和服务 nature of a resource (e.g. file vs service), as well as its spatial nature (e.g. specific file format or specific service protocol).

Resource type information is used in two ways by the pipeline controller:

1. To verify the correctness of the step-to-step pipeline stitching in an application-meaningful way. Specifically, the pipeline compilation process will verify that the resource output by one step fulfills the resource type expected as input by a downstream dependent step.
2. To inform garbage-collection of steps that provide services as their output. Specifically, if a step provides a service resource as its output, the pipeline controller will garbage-collect the step (e.g. kill its underlying container process) as soon as all dependent steps have completed their tasks. In contrast, a step which provides file resources will be garbage-collected only after it terminates successfully on its own.

A.5.1 File resources. A file resource type is described using message FileResource:

```protobuf
message FileResource {
  required bool directory = 1;
  optional string encoding = 2;
  optional string format = 3;
}
```
The file type specifies whether the resource is a file or directory, and associates with it an optional encoding and an optional format identifier.

Encoding and format identifiers are used during pipeline compilation to verify that the output resource type of a provider step fulfills the input resource type of a consumer step. In this context, if provided, the encoding and format identifiers are treated as opaque strings and are checked for exact match.

A.5.2 Service resources. A service resource type is described using message ServiceResource:

```protobuf
message ServiceResource {
  optional string protocol = 1;
}
```

The service type optionally specifies a protocol identifier. This identifier is used during pipeline compilation to ensure that the service provided by one step's output fulfills the service expectations of a dependent step's input. In this context if the protocol identifier is given on both sides, it will be verified for an exact match.

Protocol identifiers should follow a meaningful convention which, at minimum, determines the service technology (e.g. GRPC vs OpenAPI) and the service itself (e.g. using the Protocol Buffer fully-qualified name of the service definition). For example,

```
openapi://org.proto.path.to.Service/quotedbl.Var
```

A.6 Transform logic

The logic of a transform is a description (akin to a function implementation) of what a transform does and how it does it.

Transform logic is described by message TransformLogic shown below:

```protobuf
message TransformLogic {
  optional ArgumentLogic arg = 100;
  optional ReturnLogic return = 200;
  optional ContainerLogic container = 300;
  // additional logics go here, e.g.
  // optional TensorFlowLogic tensor_flow = 301;
  // optional ApacheKafkaLogic apache_kafka = 302;
  // etc.
}
```

Message TransformLogic consists of a collection of mutually-exclusive logic types captured by the message fields, of which exactly one must be set. Each logic type is implemented as a fplugin in the pipeline controller and additional logics can be added, as described in the section on architecture.

A.7 Pipeline arguments

Pipelines, like regular functions, can have arguments whose values are supplied at execution time. Unlike function argument values (which are arithmetic numbers and data structures), pipeline argument values are resource (file or service) instances.

The dedicated transform logic, called argument, is used to declare pipeline arguments.

From a pipeline graph point of view, steps based on argument transforms are vertices that have no input edges and a single output edge, representing the resource supplied to the argument when the pipeline was executed.

Message ArgumentLogic, shown below, describes a pipeline argument:

```protobuf
message ArgumentLogic {
  required string name = 1;
  required FileResource resource = 2;
}
```

Field name specifies the name of the pipeline argument. Field resource specifies the type of file or service resource expected as argument value.

Argument steps have one output in the pipeline graph, whose resource type is that provided by field resource.

A.8 Pipeline return values

Pipelines, like regular functions, can return values to the caller environment. In the case of pipelines, the returned values are resource (file or service) instances.

The dedicated transform logic, called return, is used to declare pipeline return values.

From a pipeline graph point of view, steps based on a return transform are vertices that have a single input edge, representing the resource to be returned to the pipeline caller, and no output edges.

Message ReturnLogic, shown below, describes a pipeline return value:

```protobuf
message ReturnLogic {
  required string name = 1;
  required Resource resource = 2;
}
```

Field name specifies the name of the return value. Field resource specifies the type of file or service resource returned.

Return steps have one input in the pipeline graph, whose resource type is that provided by field resource.

A.9 Container-backed transforms

A container logic describes a pipeline transform backed by a container.

Container logics are captured by message ContainerLogic shown below:

```protobuf
message ContainerLogic {
  required string image = 10;
  repeated ContainerInput inputs = 20;
  repeated ContainerOutput outputs = 21;
  repeated ContainerFlag flags = 22;
  repeated ContainerEnv env = 23;
}
```

The container logic specification captures:
(1) The identity of the container image, e.g. a Docker image label. This is captured by field image of message Container.

(2) For every named transform input and output (declared in fields inputs and outputs of message Transform), a method for passing the location of the corresponding resource (file or service) to the container on startup. Methods for passing resource location include flags and environment variables, as well as different formatting semantics, and are described later. Input and output passing methods are captured by fields inputs and outputs of message Container.

(3) Any additional startup parameters in the form of flags or environment variables. These are captured by fields flags and env of message Container.

A.9.1 Container input and output. Messages ContainerInput and ContainerOutput associate every transform input and output, respectively, with a container flag and/or environment variable, where the resource locator is to be passed to the container on startup.

```java
message ContainerInput {
  required string name = 1;
  optional string flag = 2;
  optional string env = 3;
  optional ResourceFormat format = 4;
}
message ContainerOutput {
  required string name = 1;
  optional string flag = 2;
  optional string env = 3;
  optional ResourceFormat format = 4;
}
```

Both messages have analogous semantics:
Field name matches the corresponding transform input (or output) name, as declared in message Transform within field inputs (or outputs).
Fields flag and env determine the flag name and environment variable, respectively, where the resource locator is to be passed.
Field format determines the resource locator formatting convention.
By default, file resource location is passed to the container in the form of an absolute path relative to the container’s local file system.
By default, service resource location is passed to the container using standard host and port notation.
Alternatives, are provided by message ResourceFormat.

A.9.2 Container parameters. Additional container parameters, specified in fields flags and env of message Container, are defined by message ContainerFlag below.

```java
message ContainerFlag {
  required string name = 1;
  optional string value = 2;
}
```