Implementing Cloud Agnostic Machine Learning Workflows With Apache Beam on Kubernetes

By Alexander Lerma & Charles Adetiloye

BEAM SUMMIT

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About The Presenters

Charles Adetiloye is a Cofounder and Lead Machine Learning Platforms Engineer at MavenCode. He has well over 15 years of experience building large-scale distributed applications. He has extensive experience working and consulting with several companies implementing production grade ML platforms.

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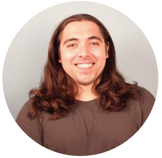

Alexander Lerma is a Machine Learning Platforms Engineer at MavenCode. He has 10 years of experience working as a Software Engineer and MLOps Engineer. Previously worked with Goldman Sachs, Twitter, and a few other startups.

twitter.com/neuralnetes

About MavenCode

MavenCode is an Artificial Intelligence Solutions Company with HQ in Dallas, Texas and remote delivery workforce across multiple time zones. We do training, product development and consulting services with specializations in:

- Provisioning Scalable AI and ML Infrastructure - OnPrem and In the Cloud
- Development & Production Operationalization of ML platforms - OnPrem and In the Cloud
- Streaming Data Analytics and Edge IoT Model Deployment for Federated Learning
- Building out Data lake, Feature Store, and ML Model Management platform

twitter.com/mavencode

Agenda for Today

1. Making the Case for Cloud Agnostic ML Deployments
2. Building it all on Kubernetes
3. Orchestration of Beam Job Deployments with Argo Workflows
4. Agile Team Approach to ML Workflow Deployment
5. Lessons Learned and Summary

Making the Case for Cloud Agnostic Machine Learning Deployments

01

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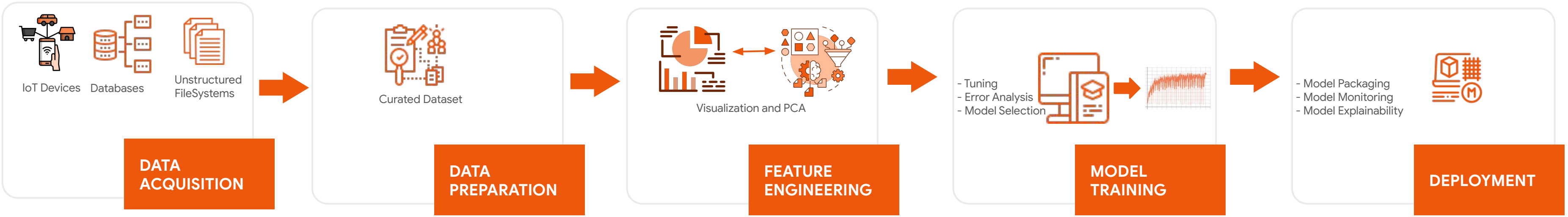
Overview of Machine Learning Workflow

1. The goal of any Machine Learning application is to build a Statistical Model using curated data and applying Machine Learning algorithms to them.

2. The main artifacts of any Machine Learning Projects are Data, ML Model and the Code.

3. This is how a Simplified ML Workflow looks



Challenges in Building ML Workflow

Reproducibility

- Not Easy to Reproduce ML Model Output on each iterative runs
- Constantly Changing Training Data
- Consistent Environment Configuration Issues

Reusability

- Training Pipelines are not Componentized for Reusability
- No well defined way of doing Model versioning and tagging
- Collaboration and sharing of source code is not well defined

Manageability

- Managing model deployment and serving between environments is difficult
- Versioning and Tracking model artifacts is very difficult and complex
- No defined way to visually track updates and changes

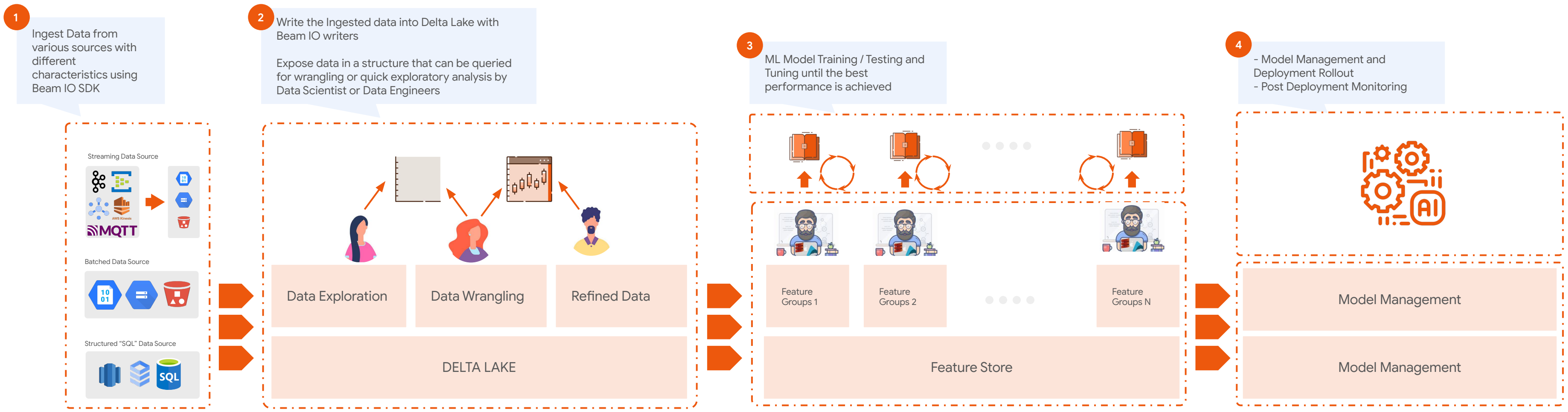
Automation

- A lot of deployment process is still manual
- Steps needed to update model parameters are not not automated
- Most data science teams are not equipped with the right knowledge to take models to production

Building ML Workflows in Reality could be Complex!

- Many Data Sources - Databases, File Systems, Storage Buckets, Streaming Data.
- The Data Sources in most cases are siloed across different locations with various access requirements: In-House datasets, Third Party, Public datasets.
- Different Data Protection Requirements - PI data, GDPR restrictions etc
- Data Availability in some cases are time-bounded! Streaming or Batched delivered Hourly, Daily, Monthly etc

Typical ML workflow in Reality is more Complex!



Our Approach to ML Workflow Deployment

- We have a Polyglot team. Use the best tool to solve the problem, as long as we can containerize it, so we have beam pipeline codes written in Go, Scala, Java and Python

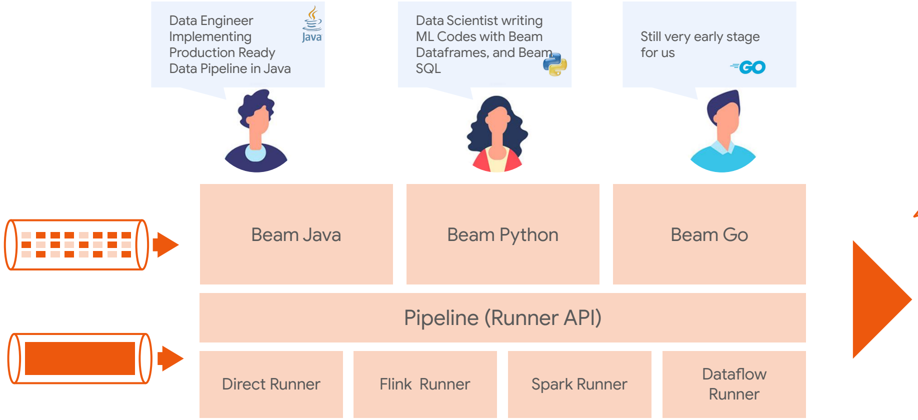
- Make use of Apache Beam's Runtime portability makes it easy for us to do local controlled testing of our ML pipelines

- We build our components to be reusable, Data Source, Data Writer, Feature Store Components, Model Training Components, and Model Serving Components

- Versioned Containerized Workflow Pipeline with Argo Workflow

- For team efficiency and consistency, we leverage Containers built on Kubernetes to gain portability across infrastructure

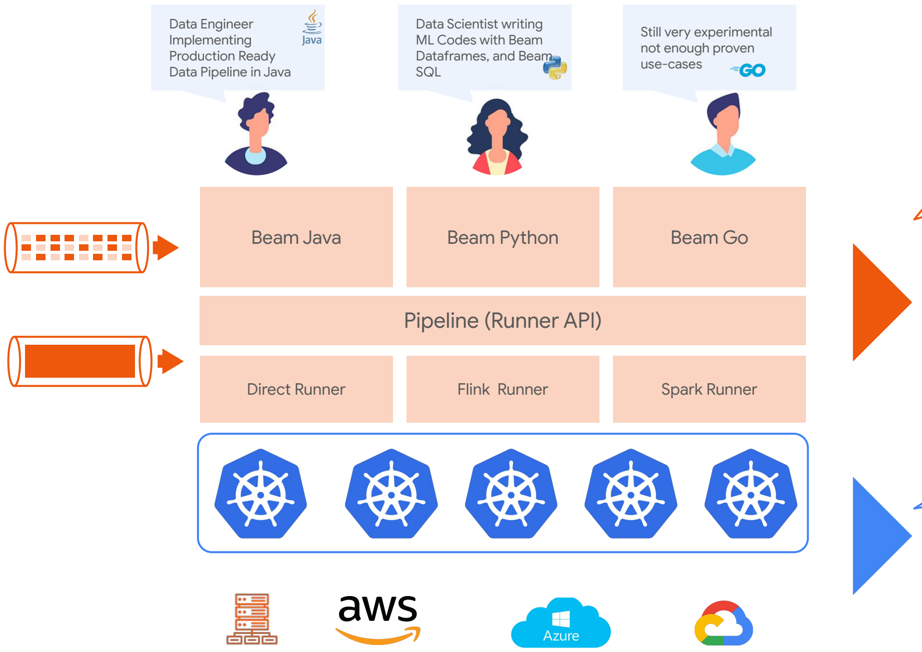
Embracing the Apache Beam Philosophy



Beam Advantage

- Unified Data Pipeline (Stream + Batch)
- Multi-Language Support (with new Portable Runner for Java/Python/Go)
- Multiple Runner Support (Direct, Flink, Spark and Dataflow)
- Beam ML, Beam Dataframe and TFX integration for ML workloads

With Kubernetes Added, ML Deployment is Easier



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Kubernetes Advantage

- Infrastructure Agnostic Setup!

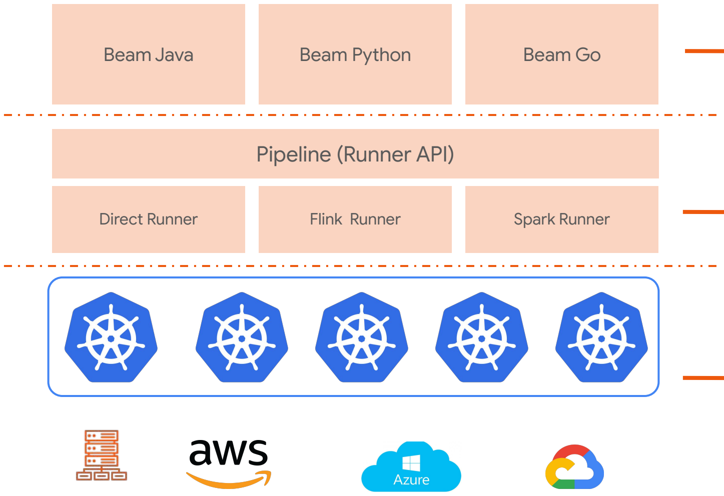
Advantages of Running Apache Beam ML Pipeline on Kubernetes

- Leverage Beams Portability, Multi-Language Semantics that now allows support for Python, Java, Scala and Golang, In addition we can use External Transforms to make calls from Python to Java Code
- Rich beam Library and API available to handle each stage of Workflow process, TFX, Beam SQL, and connector IOs
- Beam Job a can be Containerized as Unit of work that can be easily maintained on its own and deployed on the Kubernetes Cluster
- Infrastructure Portability on Kubernetes makes it easy to share or migrate between local kubernetes environment and production or development environments
- Consistency between operating environment for Data Scientist, ML Engineers and what is finally deployed
- Ease of debugging and testing on Local environment before deployment

Building it All on Kubernetes

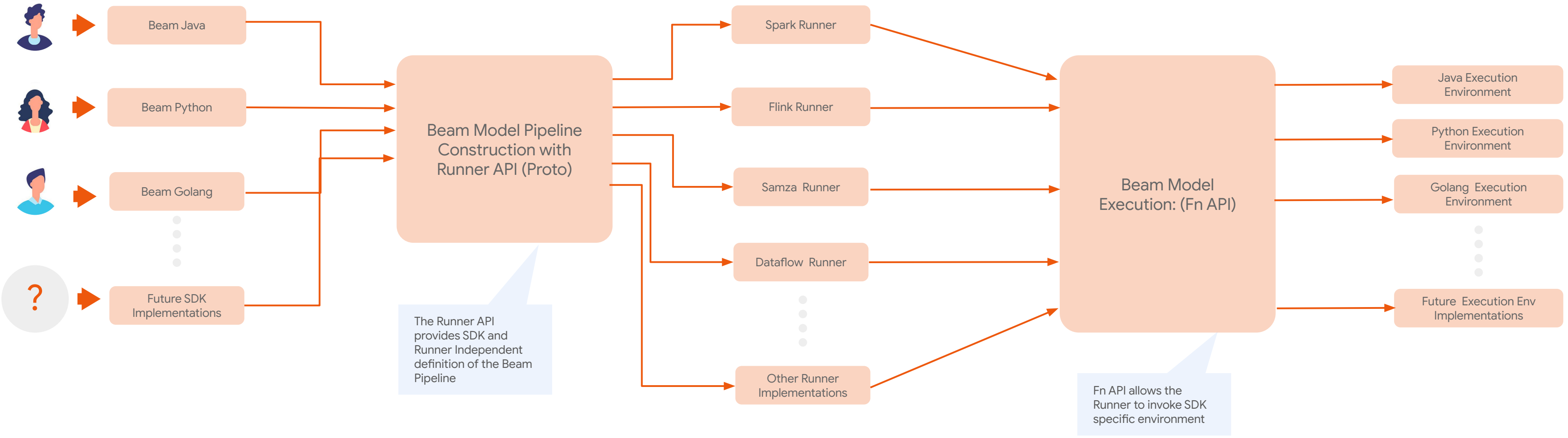
02

Building Apache Beam ML Pipeline Stack on Kubernetes

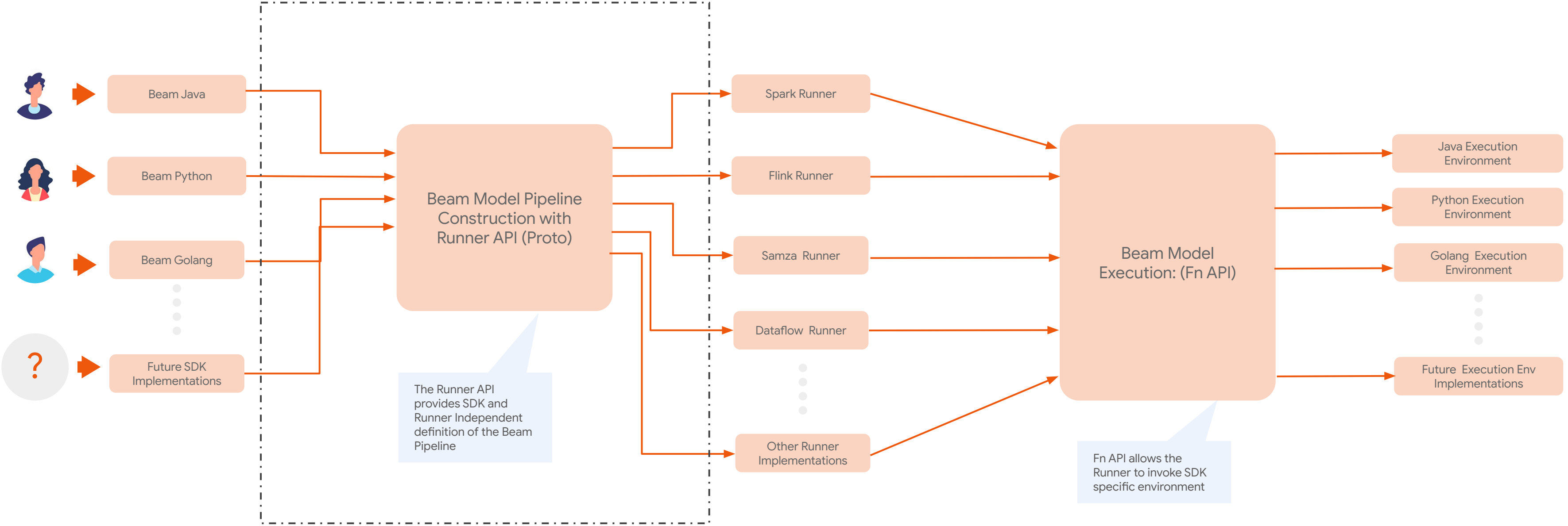


1. Portability of Coding Semantics (Java, Scala, Python, Go or SQL)
2. Portability of Across Runners (Direct Runner, Flink Runner, Spark Runner, Dataflow Runner)
3. Portability of Across Compute Infrastructure - Local Dev, OnPrem or Cloud

Portability in Apache Beam



Portability in Apache Beam



How Apache Beam Portability Works

Beam Job Example

```
import apache_beam as beam
from apache_beam.options.pipeline_options import PipelineOptions

options = PipelineOptions([
    "--runner=PortableRunner",
    "--job_endpoint=localhost:8099",
    "--environment_type=DOCKER"
])
with beam.Pipeline(options) as p:
    ...
```

1. Developer Implements Beam Job in Local Environment in this Case Python

Job Service Endpoint

```
docker run apache/beam_spark_job_server:latest
—spark-master-url=spark://<SPARK_MASTER_URL>:7077

OR

docker run apache/beam_flink1.14_job_server:latest
—flink-master=<FLINK_MASTER_URL>:8081
```

2. Starts up a Job Service Runner that targets the specific ENV they want

Deployment Clusters

3. JobService Runner Deploys Job to remote or local Spark or Flink Cluster

How Apache Beam Portability Works

Beam Job Example

```
import apache_beam as beam
from apache_beam.options.pipeline_options import
PipelineOptions

options = PipelineOptions([
    "--runner=PortableRunner",
    "--job_endpoint=localhost:8099",
    "--environment_type=LOOPBACK"
])
with beam.Pipeline(options) as p:
    ...
```

1 Developer Implements Beam Job in Local Environment in this Case Python

Job Service Endpoint

```
docker run apache/beam_spark_job_server:latest
—spark-master-url=spark://<SPARK_MASTER_URL>:7077

OR

docker run apache/beam_flink1.14_job_server:latest
—flink-master=<FLINK_MASTER_URL>:8081
```

2 Starts up a Job Service Runner that targets the specific ENV they want

3 JobService Runner Deploys Job to remote or local Spark or Flink Cluster

Deployment Clusters

APACHE Spark

kubernetes

OR

minikube

Beam Portability Advantages

- Rich set of IOs already implemented In Beam Java can be invoked in Python, GO etc

```
from apache_beam.options.pipeline_options import PipelineOptions
from apache_beam.io.kafka import ReadFromKafka

p = beam.Pipeline(options=pipeline_options)
res = (p | 'ReadFromKafka' >> ReadFromKafka(consumer_config={"bootstrap.servers": "localhost:9092"},topics=["<TOPICS>"])
```

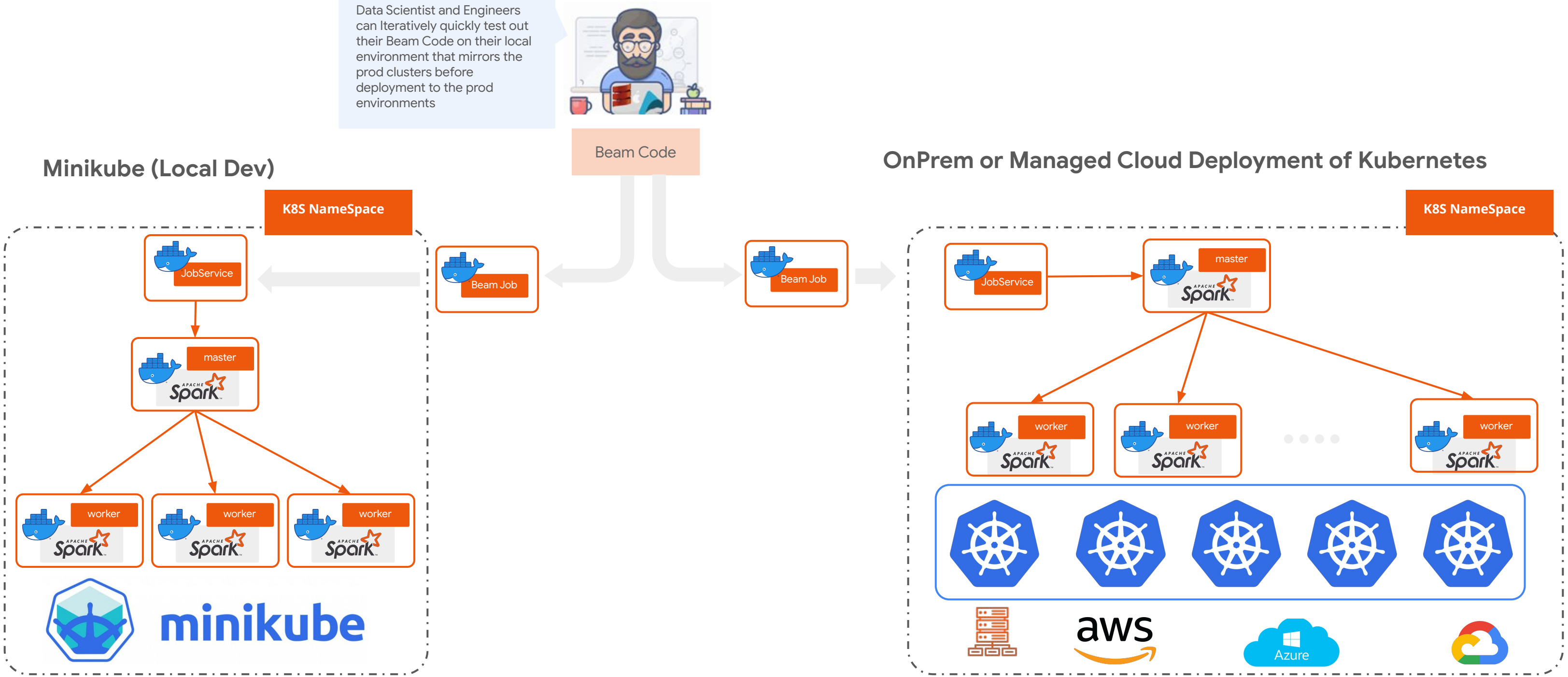
- Using Expansion Service with External Transforms to call Java APIs

```
from apache_beam.options.pipeline_options import PipelineOptions
from apache_beam.io.kafka import ReadFromKafka

p = beam.Pipeline(options=pipeline_options)
res = (p | 'ReadFromKafka' >> ReadFromKafka(consumer_config={"bootstrap.servers": "localhost:9092"},topics=["<TOPICS>"]
        | 'ReadFromKafka' >> beam.JavaExternalTransform("org.apache.beam.sdk.io.TextIO").write().to("<STORAGE_PATH>")
```

Infrastructure Portability on Kubernetes with Apache Spark

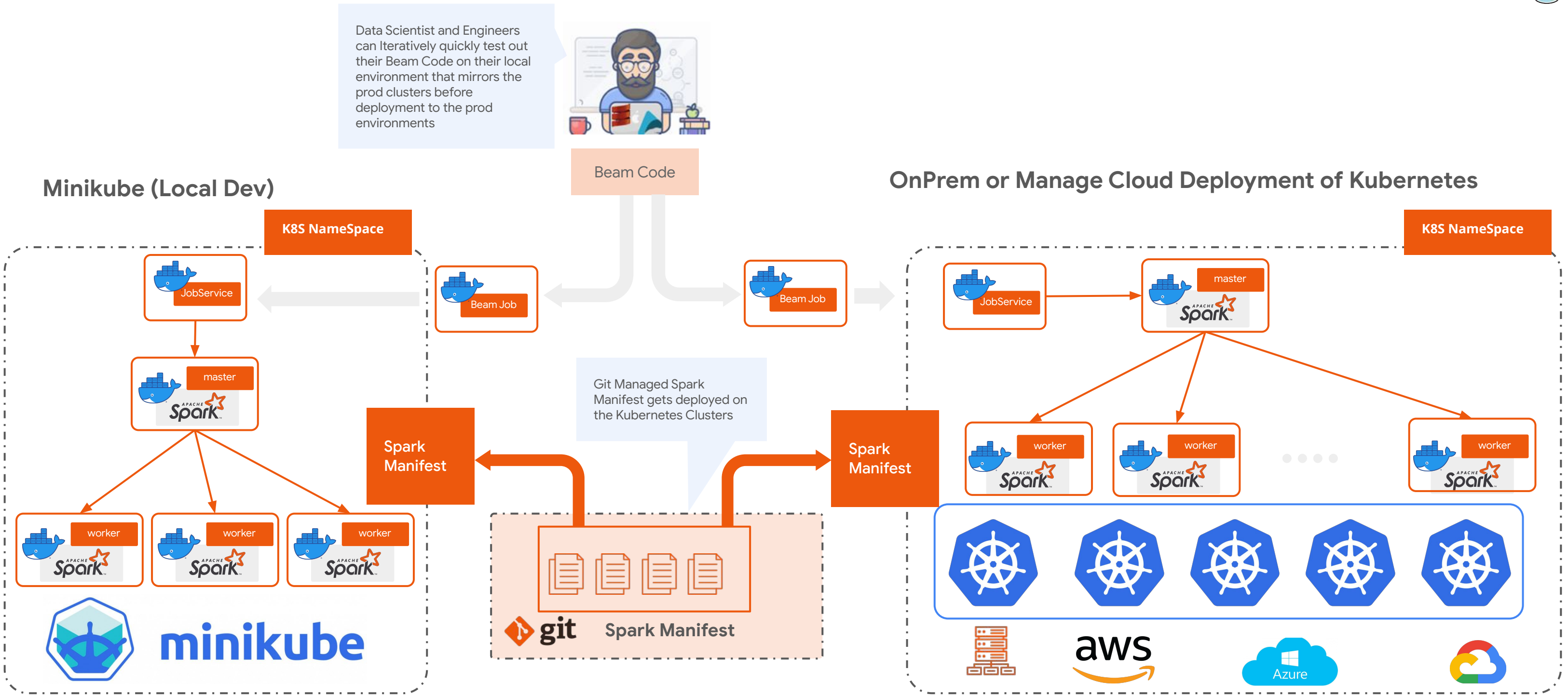
Data Scientist and Engineers can Iteratively quickly test out their Beam Code on their local environment that mirrors the prod clusters before deployment to the prod environments



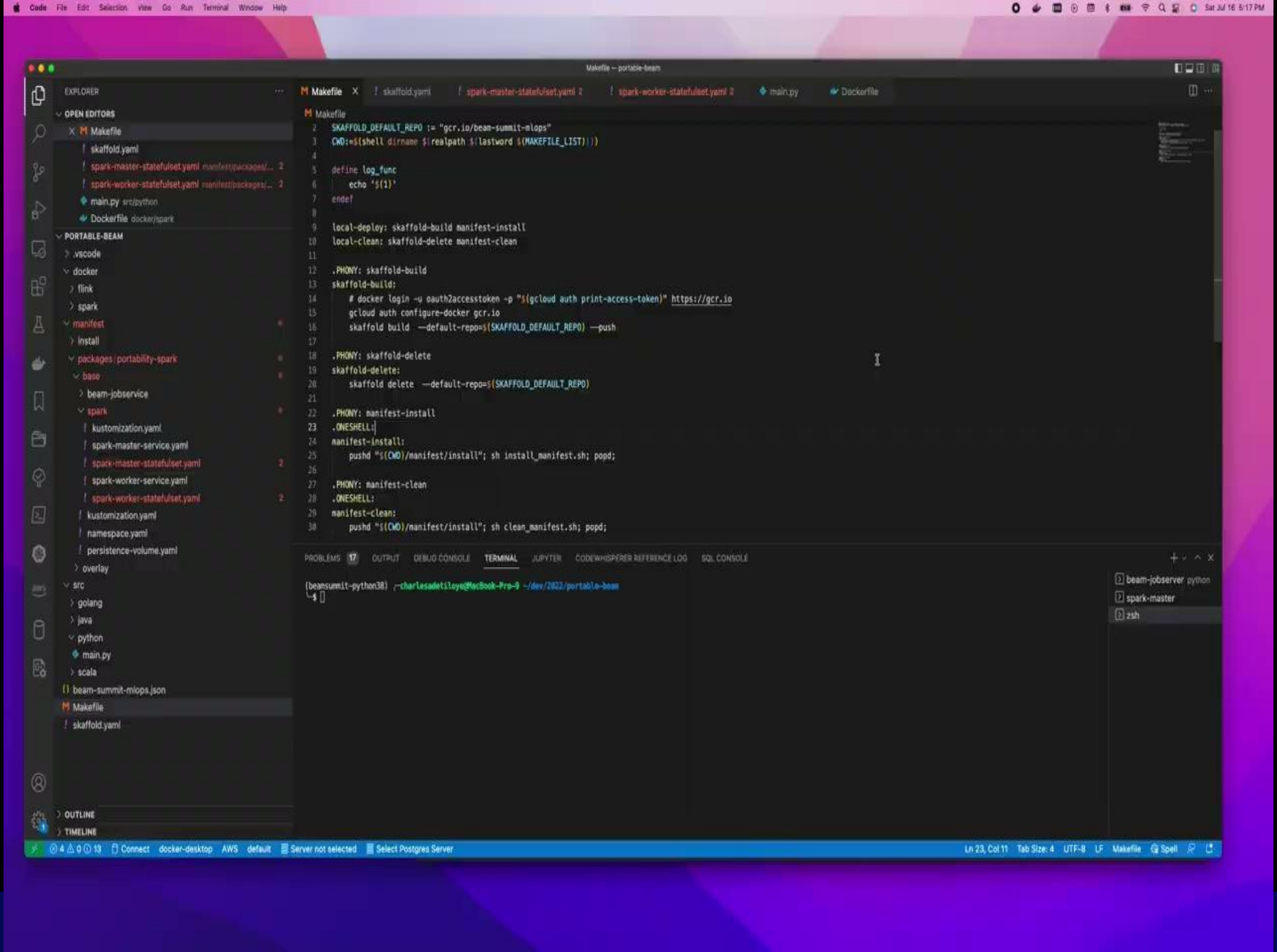
Pipeline Package Management and Deployment on Kubernetes with Kustomize

- The Spark/Flink Runner Cluster deployment process is managed with Kustomize, making it easy to version control and manage the deployment via GitOps process
- We can target different deployment environment with Kustomize overlay that overrides the base configuration, allowing us to deploy across multiple environments
- We can use Kustomize configuration to target various Kubernetes Infrastructure - OnPrem, AWS, GCP, Azure
- It is easy to progressively extend and manage various version of packages that is trackable via git release

Infrastructure Portability with Kubernetes (Apache Spark)



Overview and Quick Demo of How it All fits together


Makefile
SKAFFOLD_DEFAULT_REPO := "gcr.io/beam-summit-mlops"
CWD:=$(shell dirname $(realpath $(lastword $(MAKEFILE_LIST))))
define log_func
echo '$(1)'
endef
local-deploy: skaffold-build manifest-install
local-clean: skaffold-delete manifest-clean
.PHONY: skaffold-build
skaffold-build:
docker login -u oauth2accesstoken -p "$(gcloud auth print-access-token)" https://gcr.io
gcloud auth configure-docker gcr.io
skaffold build --default-repo=$(SKAFFOLD_DEFAULT_REPO) --push
.PHONY: skaffold-delete
skaffold-delete:
skaffold delete --default-repo=$(SKAFFOLD_DEFAULT_REPO)
.PHONY: manifest-install
.ONESHELL:
manifest-install:
pushd "$(CWD)/manifest/install"; sh install_manifest.sh; popd;
.PHONY: manifest-clean
.ONESHELL:
manifest-clean:
pushd "$(CWD)/manifest/install"; sh clean_manifest.sh; popd;
PROBLEMS
OUTPUT
DEBUG CONSOLE
TERMINAL
JUPYTER
SQL CONSOLE

So with Apache Beam and Kubernetes …

- We gain Portability across our development environments
- Easily leverage the functionalities of all the extensive Apache Beam Libraries especially Java
- We use Kustomize Manifest to Deploy the Spark or Flink Clusters on Kubernetes

Orchestration of Beam Job Deployment with Argo Workflows

03

Implementing ML Workflow Pipelines on Kubernetes

We have achieved Portability of Code and Portability of Infrastructure!

But beyond that we need to create Workflows that can chain "Tasks" that we need to execute together and while also enforcing the dependencies between them

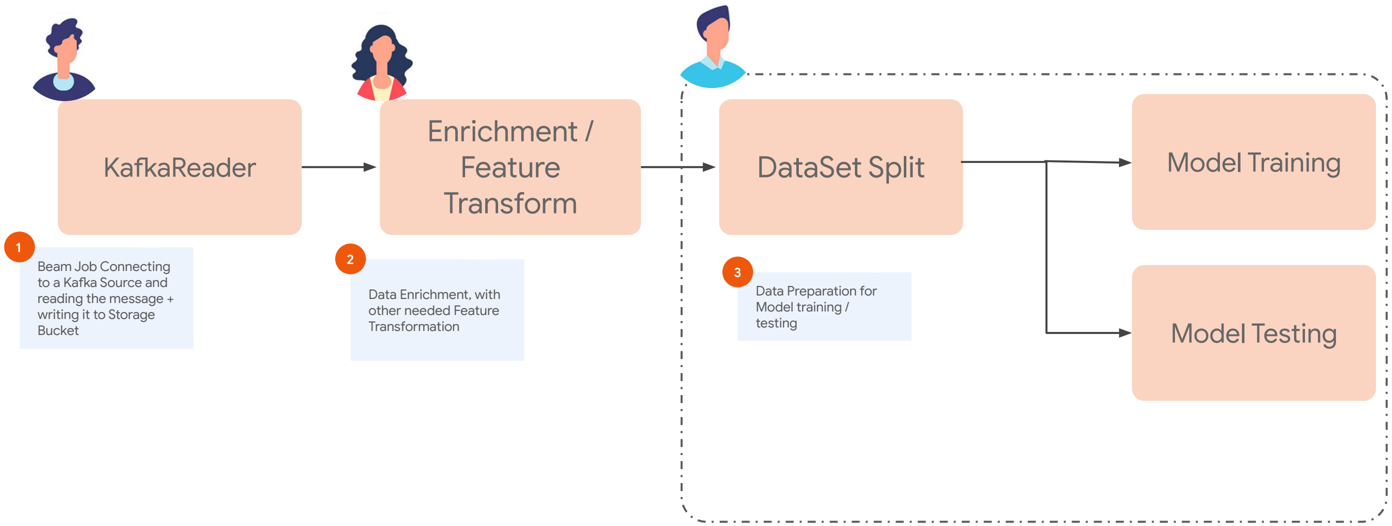
Introducing Argo Workflow for Orchestrating Workflows

Argo Workflow is a open source container-native workflow engine for orchestrating parallel jobs on Kubernetes

Why Use Argo Workflow with Beam?

- Runs natively on Kubernetes
- We can define each stage of Beam Job as a task that runs in it’s own container
- The Argo Workflow abstraction makes it easy for us to create multi-step tasks with varying availability and latencies
- Easy to compose complex tasks as a series of steps and because it’s running on kubernetes, it’s easily portable across infrastructure

Implementing Argo Workflow for Beam Jobs



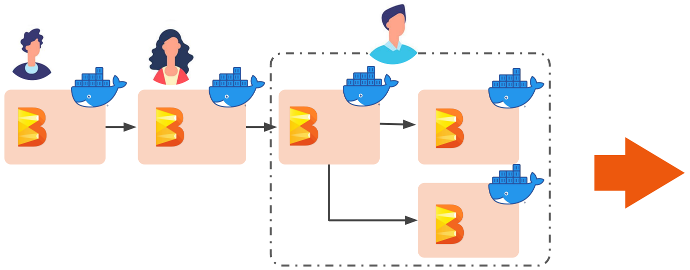
- ML Engineers / Data Scientists are responsible for different components

- The Components are containerized and Tagged as a Beam Job (or Any other Job type)

- Argo DSL will be used to compose the Pipeline DAG and Graph

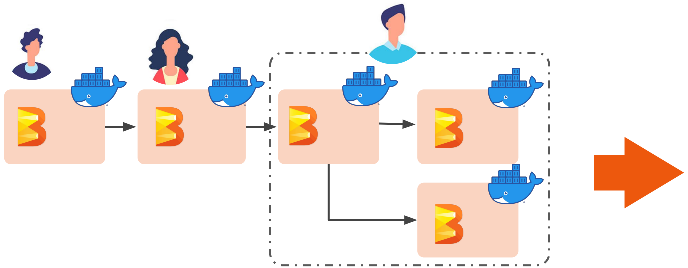
Implementing Argo Workflow for Beam Jobs

Argo Workflow DAG

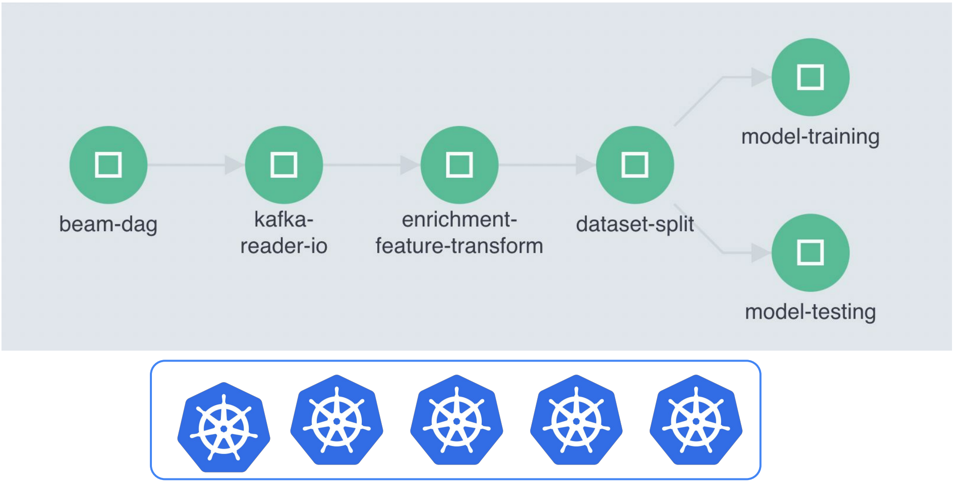


```yaml
apiVersion: argoproj.io/v1alpha1
kind: Workflow
metadata:
  name: beam-dag
spec:
  entrypoint: main
  templates:
   - name: main
     dag:
       tasks:
         - name: kafka-reader-io
           template: kafka-reader-io
         - name: enrichment-feature-transform
           depends: kafka-reader-io
           template: enrichment-feature-transform
         - name: dataset-split
           depends: enrichment-feature-transform
           template: dataset-split
         - name: model-training
           depends: dataset-split
           template: model-training
         - name: model-testing
           depends: dataset-split
           template: model-testing
   - name: kafka-reader-io
     container:
       image: gcr.io/beam-summit-mlops/kafka-reader-io:latest
   - name: enrichment-feature-transform
     container:
       image: gcr.io/beam-summit-mlops/enrichment-feature-transform:latest
   - name: dataset-split
     container:
       image: gcr.io/beam-summit-mlops/dataset-split:latest
   - name: model-training
     container:
       image: gcr.io/beam-summit-mlops/model-training:latest
   - name: model-testing
     container:
       image: gcr.io/beam-summit-mlops/model-testing:latest
```

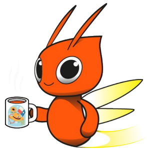
Implementing Argo Workflow for Beam Jobs



Argo Workflow DAG



Using Argo Events to Trigger Beam Pipeline Workflows

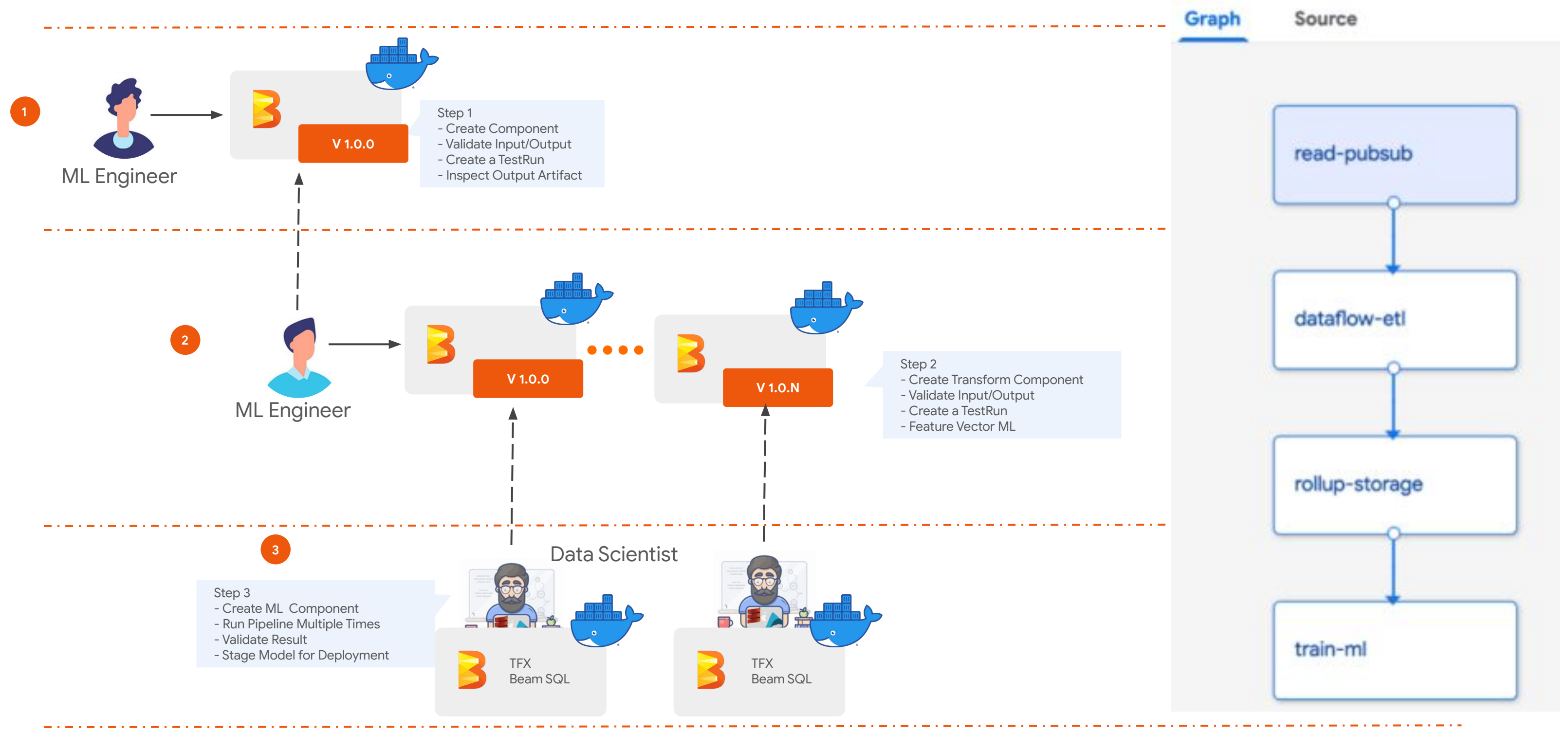


- Allows for dynamic creation of Argo Workflows to run our beam jobs
- Allows for various event trigger sources such as kafka or calendar events (cron jobs)
- You can combine workflows based on conditional triggers
- Cloud agnostic, not tied to any managed service
- Kubernetes native
- Portable across infrastructures

Agile Team Development Approach to ML Workflow Deployment

04

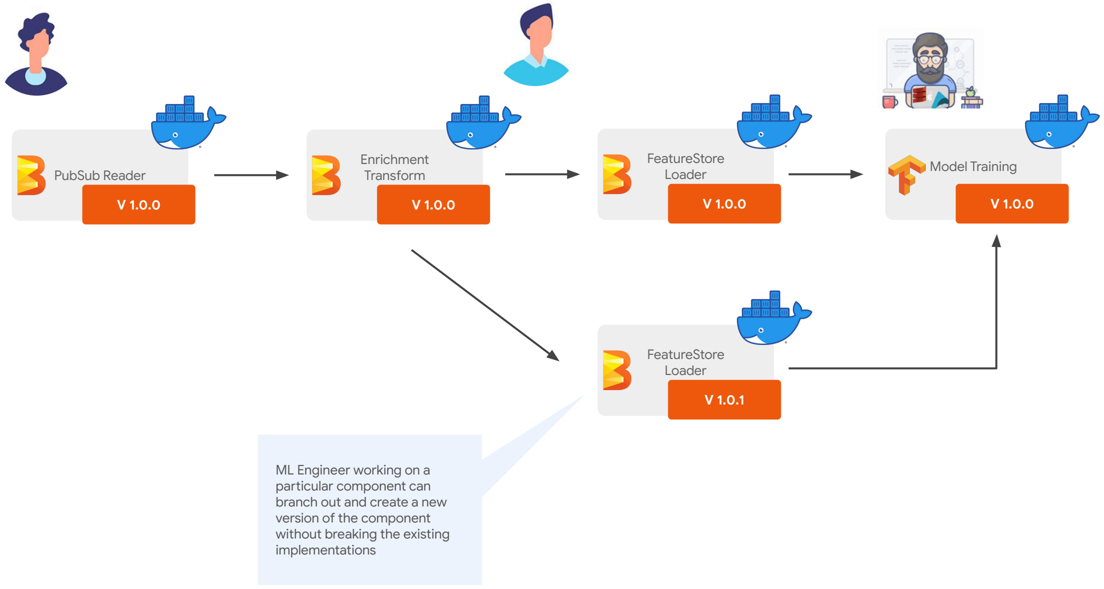
Collaborative ML Component Pipeline Development



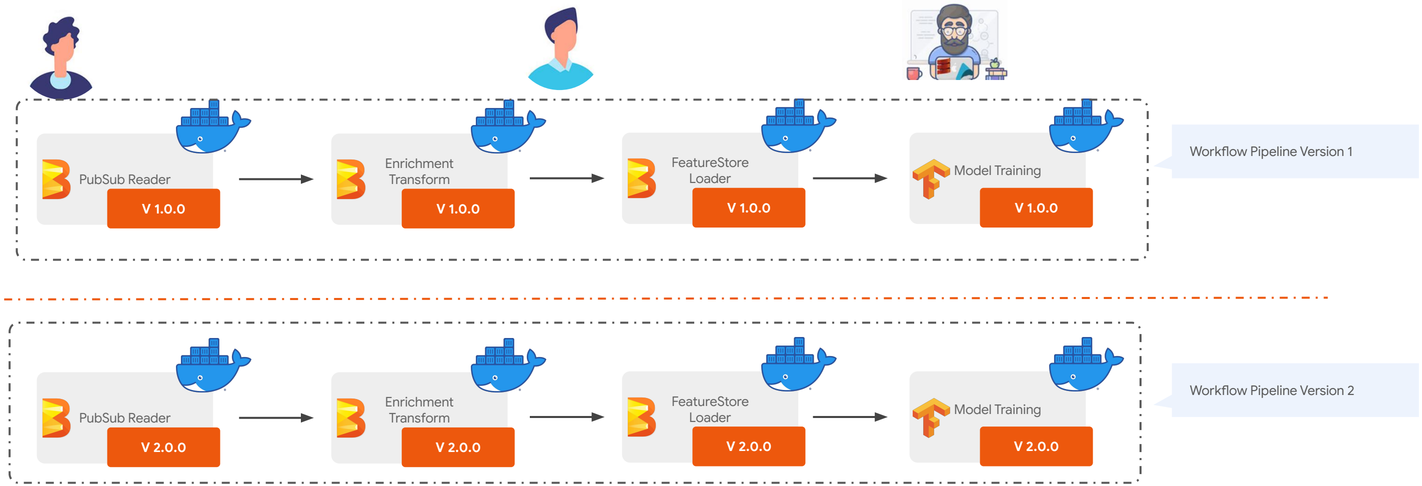
Collaborative ML Component Pipeline Development

- Each Beam Job runs in Container as manageable Unit
- The Container is versioned / Tracked with other artifacts needed for the deployment
- Pipeline for the Workflow is implemented in Argo and also tracked and versioned
- The output artifact from the Pipeline run is saved with the Pipeline Run Version ID

Argo Workflow ML Pipeline Components (Versioning)



Argo Workflow ML Pipeline Workflow (Versioning)



Lessons Learned and Summary

05

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Challenges in Building ML Workflow

Rep ducibility

- Not Ea Reprod L Model Output on each it ve
- Constantly C ng Training Data
- Consistent ent Configuration Issues

- Using Argo Workflow
- Kubernetes

Reusa ity

- Training Pi es are Componentiz sability
- No well defined f doing Model versioning a gg
- Collabora and shar f source code i well defined

- Containerization with Docker
- Argo Workflow Pipeline
- Leveraging Beam APIs

Manage lity

- Managing mo oyment and serving between envi s is difficult
- Versioning rack odel artifacts is very dif and comp
- No d ed way to visually updates a anges

- Beam Portability
- Infrastructure Portability with Kubernetes
- Argo Workflows
- Configurable Runners

Auton ion

- A lot of de ent ss is still manual
- Steps needed t ate model parameters a automated
- Most data ce te are not equippe n the right wledge to take r s to production

- GitOps
- Kubernetes

Lessons Learned + Summary

- Apache Portable Runner Implementation blueprint is very solid even though it’s evolving, it makes easy for us to quickly test our implementations on a small scale before production deployment

- We are able to leverage Apache Beam / Kubernetes development environment setup to make it easy for Data Scientist, ML engineers, Data Engineers to easily collaborate on our team

- Version of SDKs, JobService Containers etc, could easily get mismatched, It’s always advisable to have a CI environment for testing releases

- Aside from the initial overhead of getting the environment setup, our productivity and team efficiency increased significantly

- Cloud is not Cheap, we can easily manage our compute resource utilization

Q & A!

Thanks for Coming :-) !

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