TensorFlow

ML Inference at scale, easy as learning your 5 X table!

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Google

ML Inference at scale, easy as learning your 5 times table, with TFX and Apache Beam!

TensorFlow

Production Machine Learning

Agenda

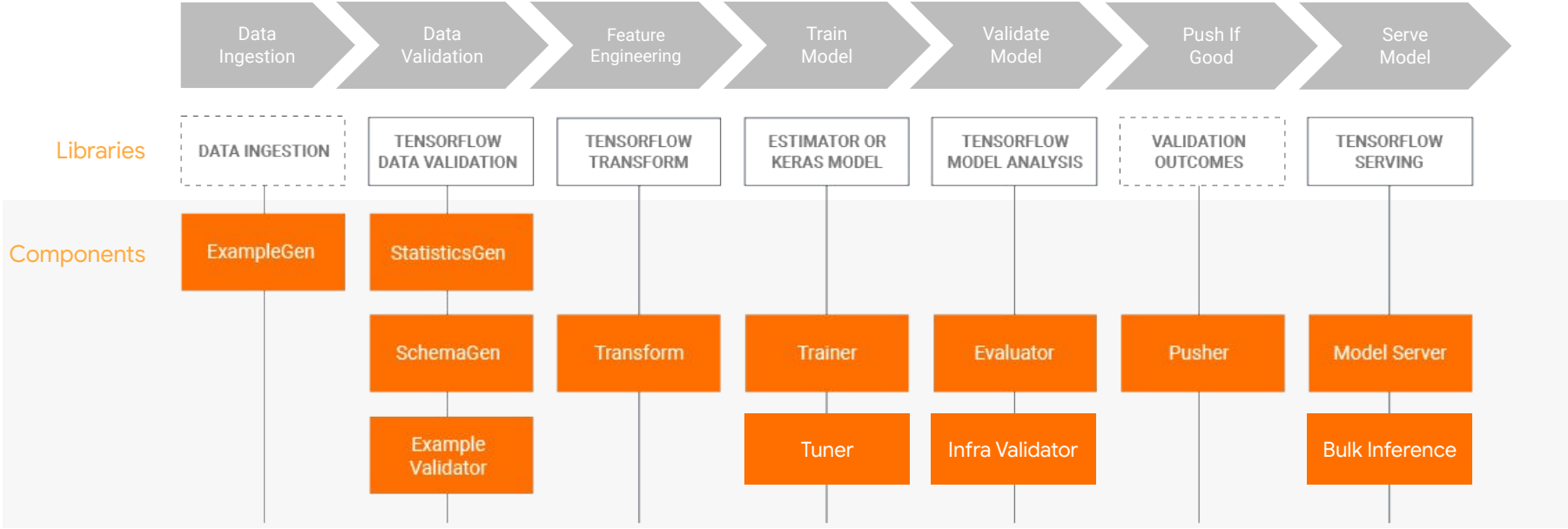
1. Overview of RunInference and its place within TFX ML-OPS
2. Doing our 5 times table, with Apache Beam and RunInference
3. Pre and Post-processing
4. Branching and sequential inference pipelines
5. GPUs with the Dataflow Runner

TFX / RunInference- Quick Overview

TensorFlow

Machine Learning & Pipelines

ML development falls naturally into a series of tasks



What do we mean by portability?

TFX runs just about anywhere

Execution

Orchestration

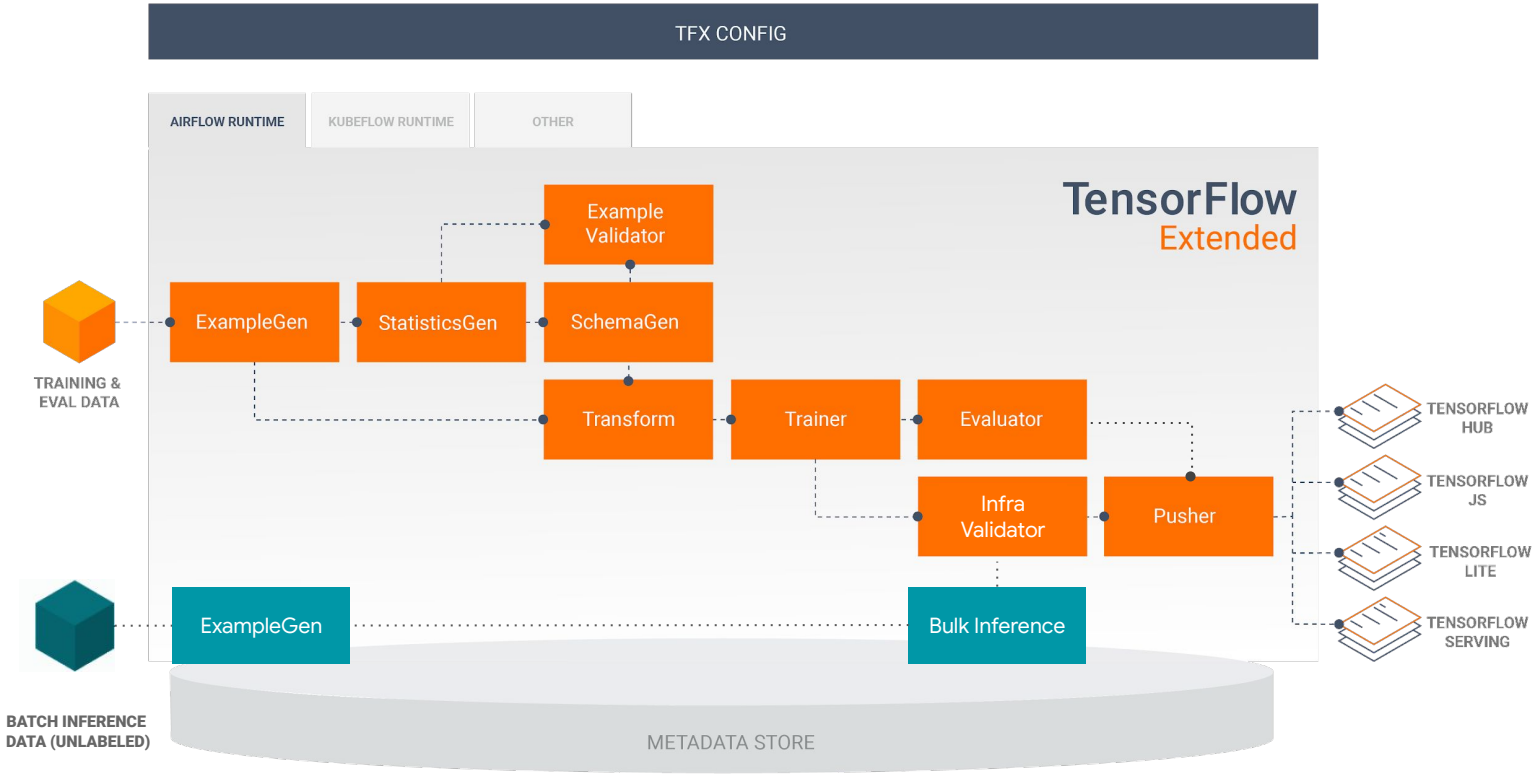
Processing

Why is portability important?

Meet the user's needs, instead of requiring them to meet yours

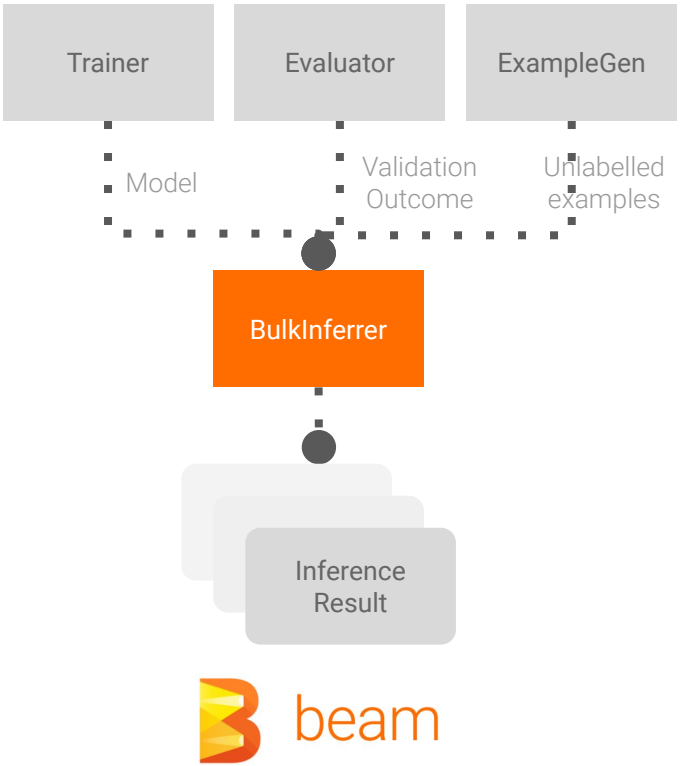
- Execution environments
- Orchestrators
- Distributed processing frameworks
- Languages (to some extent)
- Teams / Business units

Hello TFX


TFX CONFIG
AIRFLOW RUNTIME
KUBEFLOW RUNTIME
OTHER
TensorFlow
Extended
Example Validator
ExampleGen
StatisticsGen
SchemaGen
Transform
Trainer
Evaluator
Infra Validator
Pusher
TRAINING & EVAL DATA
ExampleGen
Bulk Inference
BATCH INFERENCE DATA (UNLABELED)
METADATA STORE
TENSORFLOW HUB
TENSORFLOW JS
TENSORFLOW LITE
TENSORFLOW SERVING

Component: BulkInferrer

Inputs and Outputs



Configuration

```
bulk_inferrer = BulkInferrer(
    examples=inference_example_gen.outputs['examples'],
    model_export=trainer.outputs['output'],
    model_blessing=evaluator.outputs['blessing'],
    data_spec=bulk_inferrer_pb2.DataSpec(
        example_splits=['unlabelled']),
    model_spec=bulk_inferrer_pb2.ModelSpec())
```

Configuration Options

Block batch inference on a successful model validation.
Choose the inference examples from example gen's output.
Choose the signatures and tags of inference model.

Inference Result

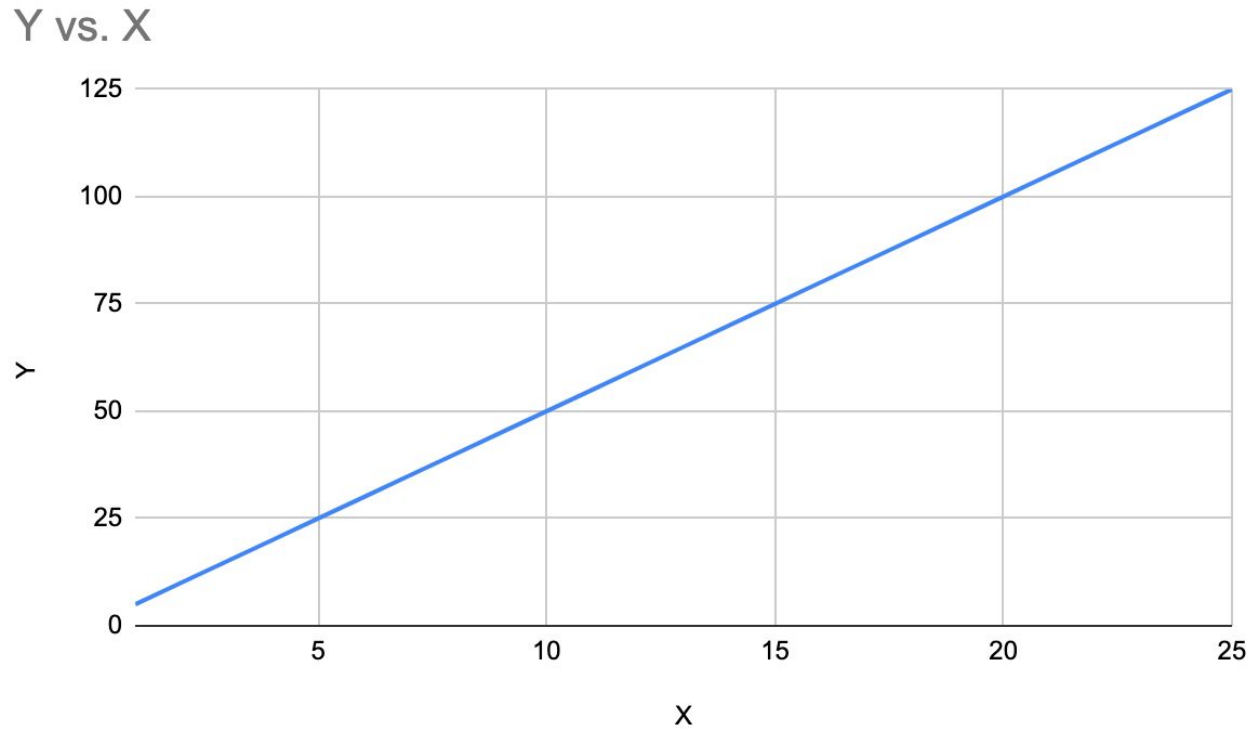
Contains features and predictions.

BulkInferrer & RunInference

TFX components run data processing in Beam pipelines

- BulkInferrer runs inference on Beam using RunInference
- RunInference included in `tensorflow/tfx-bsl`
- RunInference can also be used in pure Beam
  - Beam pipelines with no TFX
  - Beam pipelines inside TFX custom components

A simple model



What can you do with a model?

Imagine trying to do these without a model!

- Speech to text
- Text to customer sentiment
- Recognize objects in images
- Look for manufacturing defects in images
- Predict failures in equipment
- Select the products that a customer is most likely to want
- Select the support doc that fixes a customer issue

```
"""
Build a simple linear regression model.
Note the model has a shape of (1) for its input layer, it will expect a
single int64 value.
"""

input_layer = keras.layers.Input(shape=(1), dtype=tf.float32, name='x')

output_layer= keras.layers.Dense(1)(input_layer)

model = keras.Model(input_layer, output_layer)

model.compile(optimizer=tf.optimizers.Adam(), loss='mean_absolute_error')

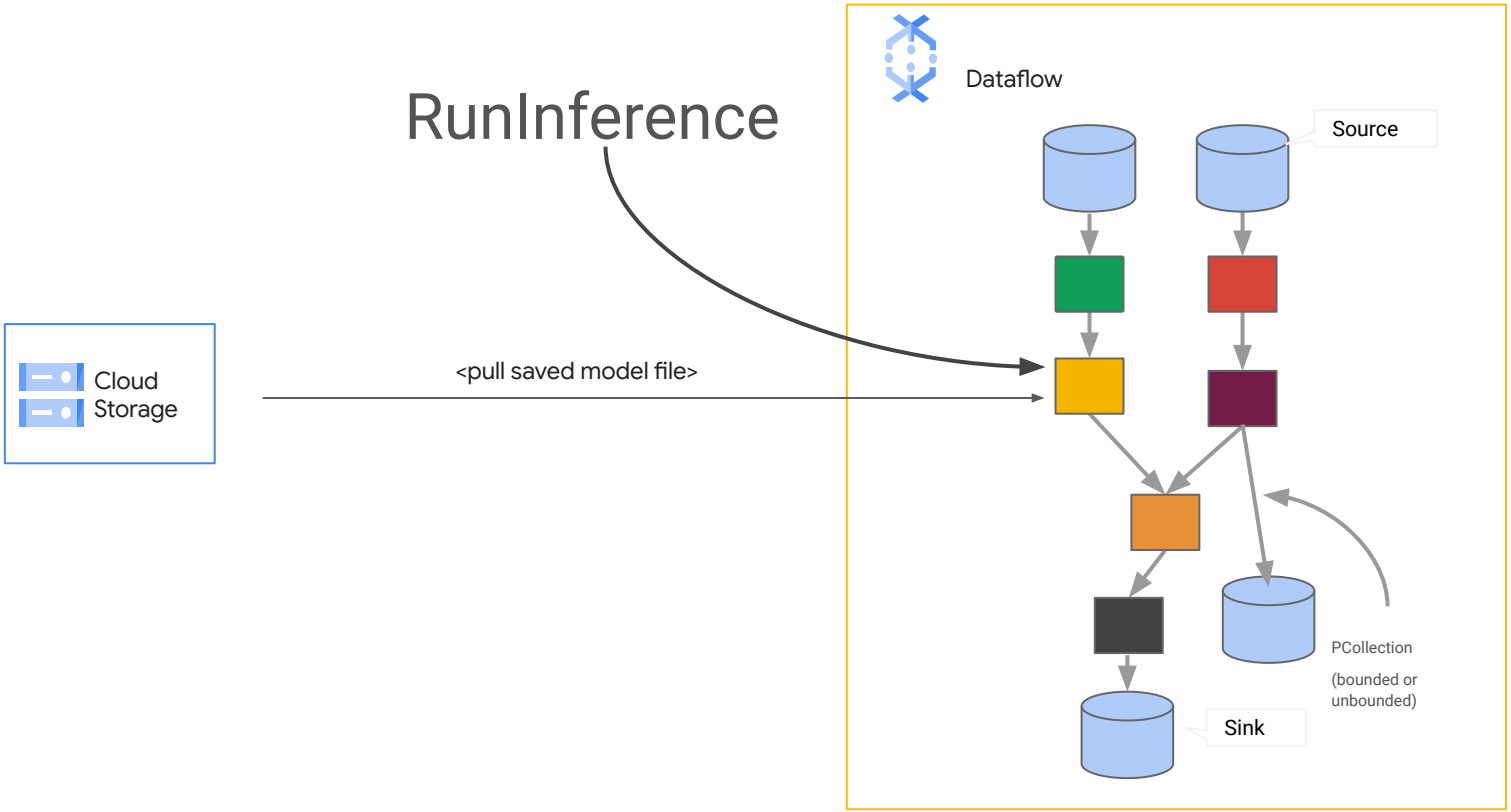
model.summary()
```

tfx_bsl.public.beam.RunInference

Features

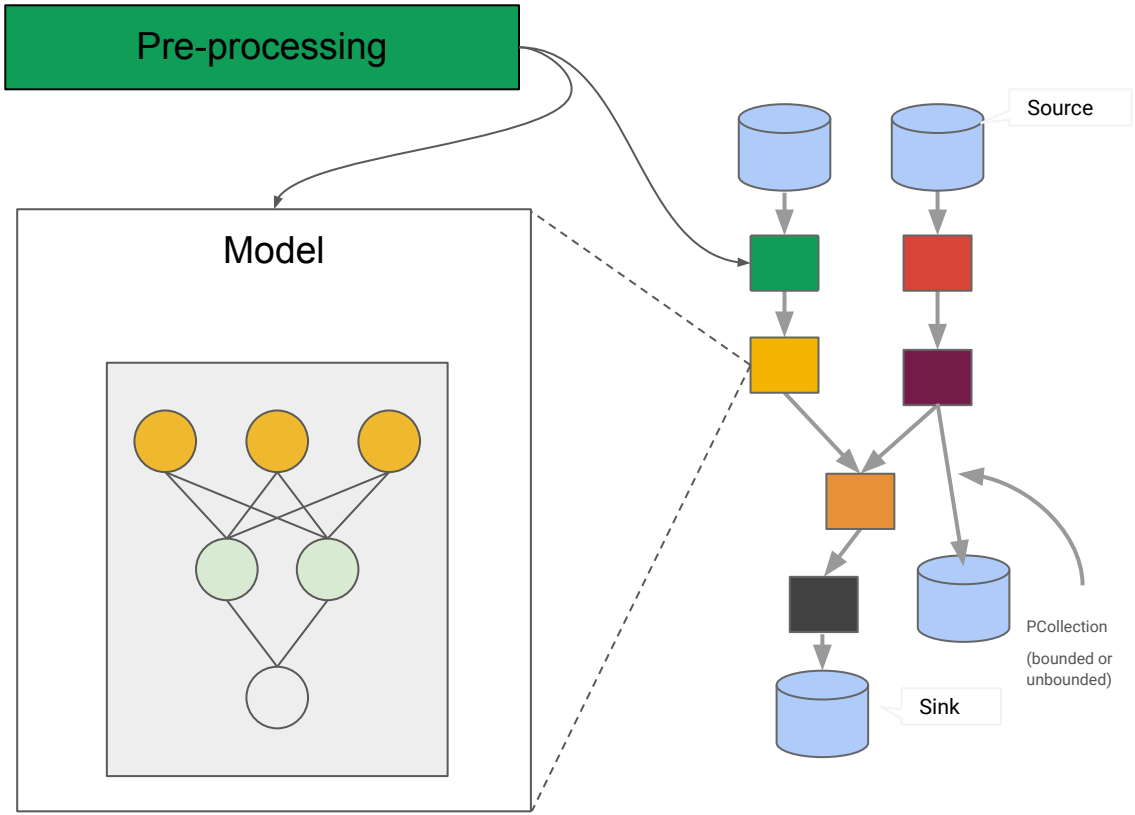
- Batches inputs when possible
- Outputs a predictlog proto, includes input
- Key forwarding
- Remote or Local mode
- Local mode, loads the model once and shares across threads

RunInference - Local model mode



Pre-processing choices

Dataflow



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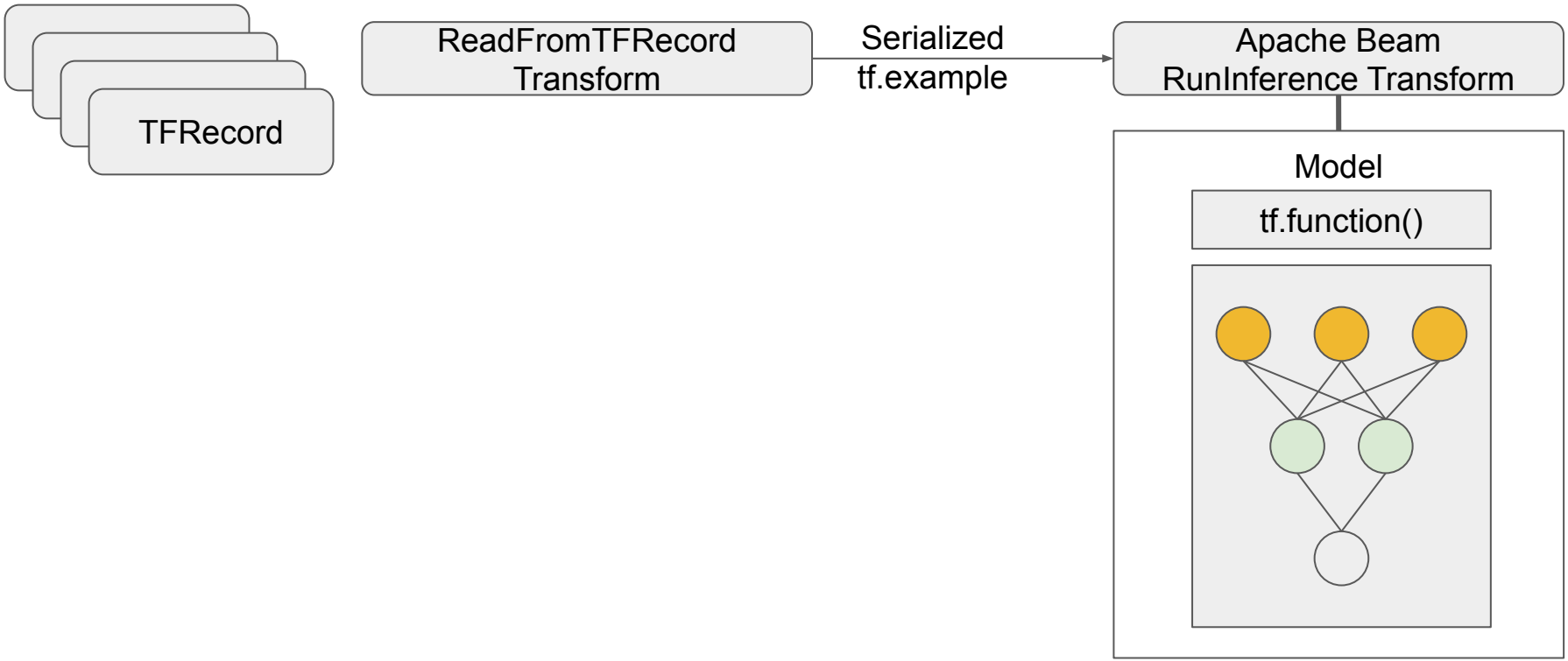
```

The serving signature



Change the input to the model

```
@tf.function(input_signature=[tf.TensorSpec(shape=[None], dtype=tf.string , name='examples')])
def serve_tf_examples_fn(serialized_tf_examples):
    """Returns the output to be used in the serving signature."""
    features = tf.io.parse_example(serialized_tf_examples, RAW_DATA_PREDICT_SPEC)
    return model(features, training=False)

signature = {'serving_default': serve_tf_examples_fn}

tf.keras.models.save_model(model, save_model_dir_multiply, signatures=signature)
```

Notebook

DEVELOPERS & PRACTITIONERS

Using TFX inference with Dataflow for large scale ML inference patterns

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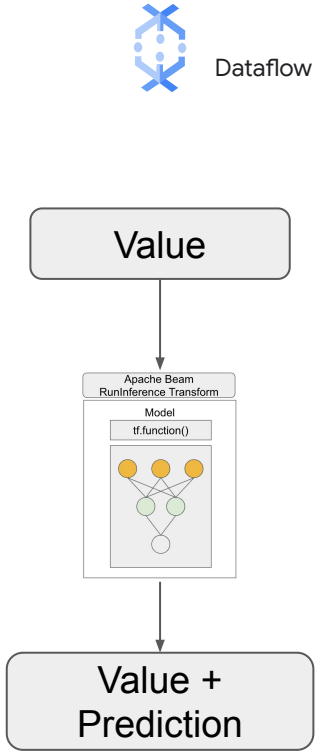
April 29, 2021

In part I of this blog series we discussed best practices and patterns for efficiently deploying a machine learning model for inference with Google Cloud Dataflow. Amongst other techniques, it showed efficient batching of the inputs and the use of shared.py to make efficient use of a model.

Metadata - Attaching a key



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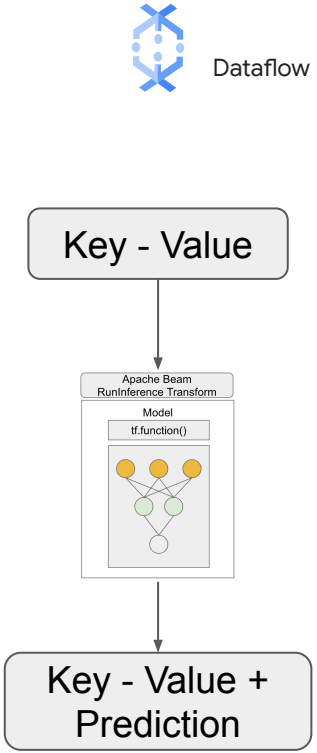


Metadata - Attaching a key

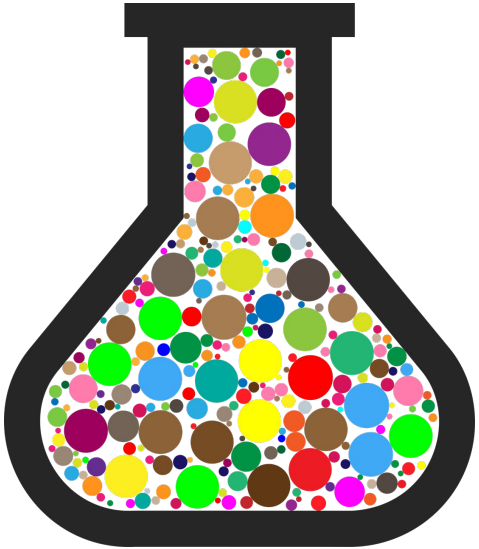
- PCollection[bytes] -> PCollection[PredictionLog]
- PCollection[Tuple[K, bytes]] -> PCollection[Tuple[K, PredictionLog]]

- PCollection[Example] -> PCollection[PredictionLog]
- PCollection[Tuple[K, Example]] -> PCollection[Tuple[K, PredictionLog]]
- PCollection[Tuple[K, SequenceExample]] -> PCollection[Tuple[K, PredictionLog]]

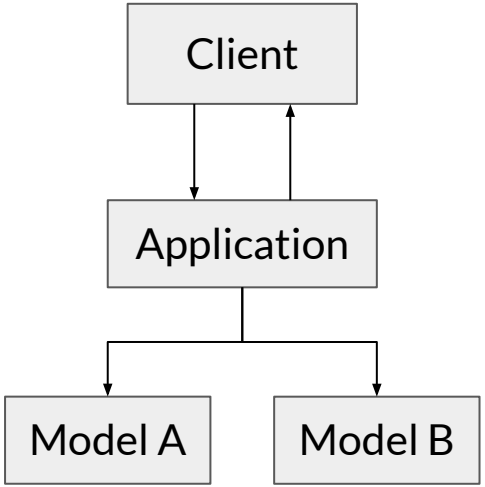
Notebook

Live Experimentation

- Model metrics are usually not exact matches for business objectives
- Example: Recommender systems
  - Model trained on clicks
  - Business wants to maximize profit
  - Example: Different products have different profit margins



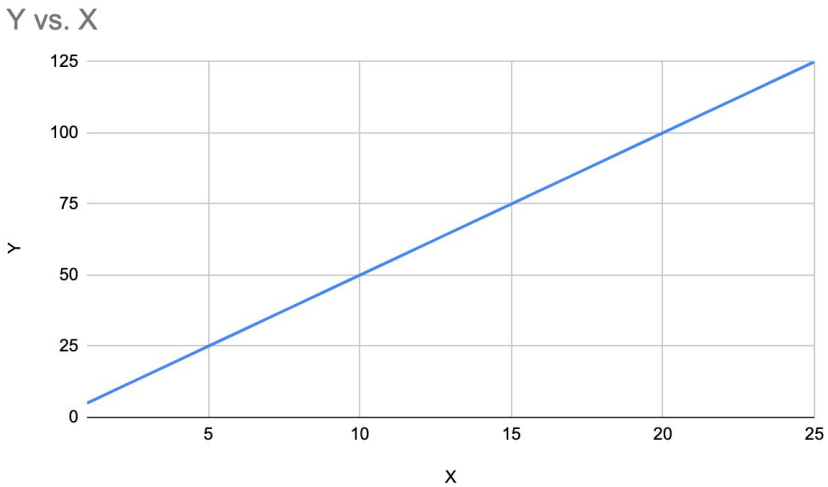
Live Experimentation - A/B Testing



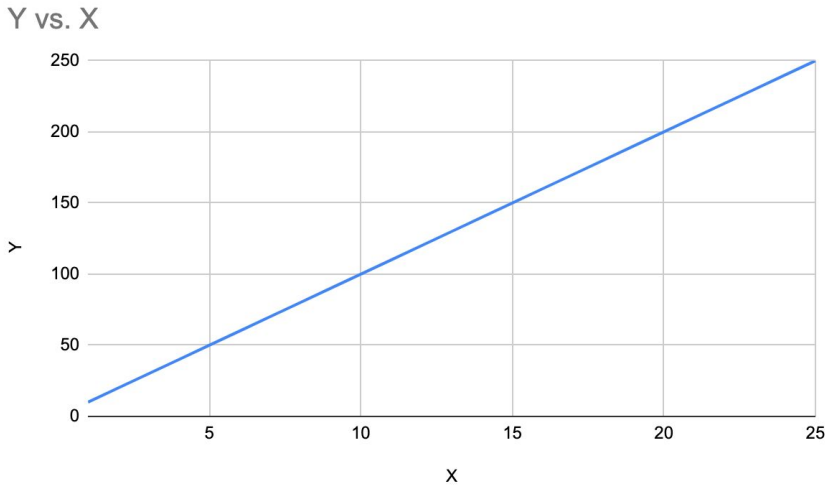
- Users are divided into two groups
- Users are randomly routed to different models in environment
- You gather business results from each model to see which one is performing better

Multiple Models

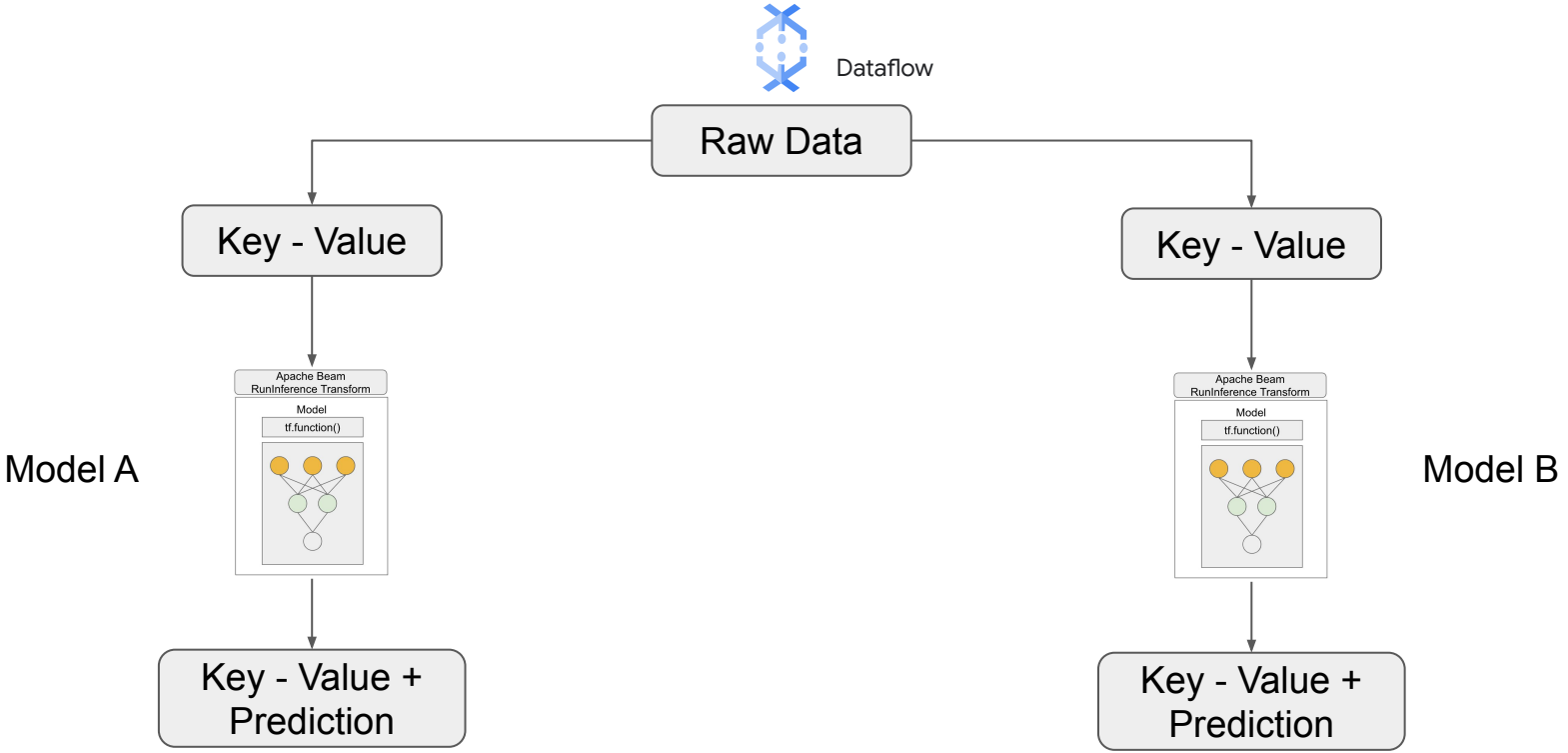
y=5x



y=10x



Multiple Models



Cascade Ensembles: Model > Model

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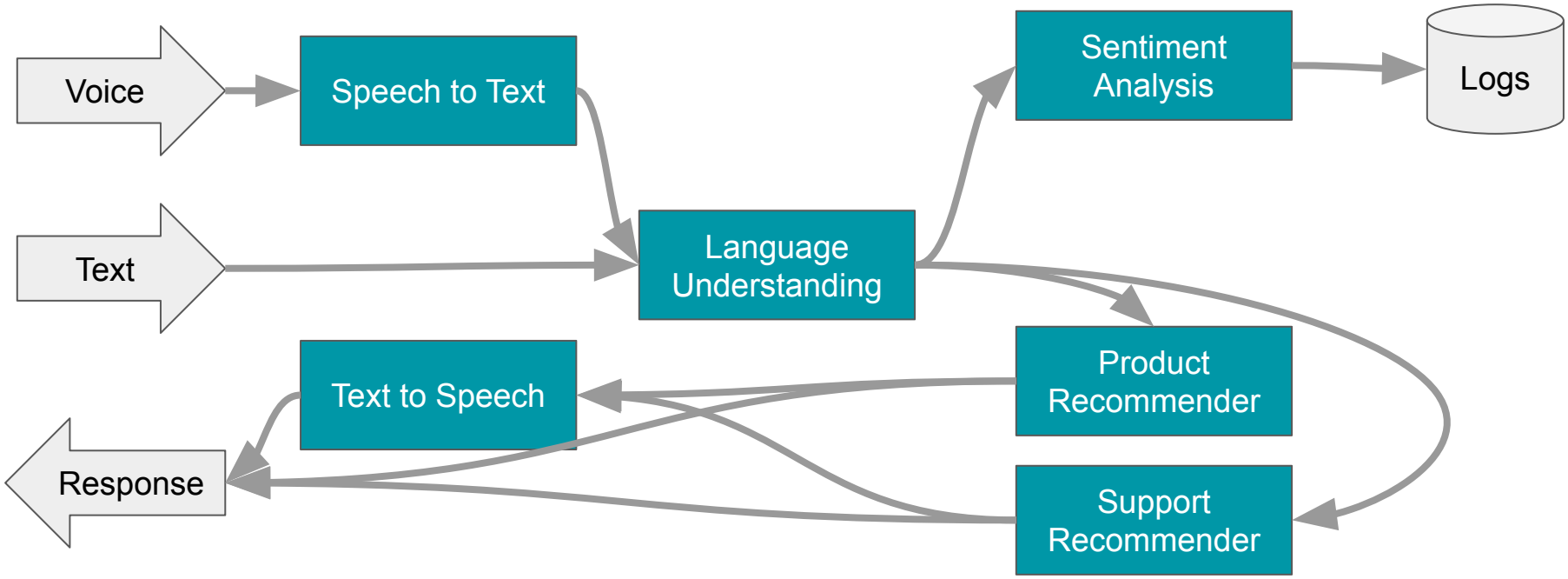
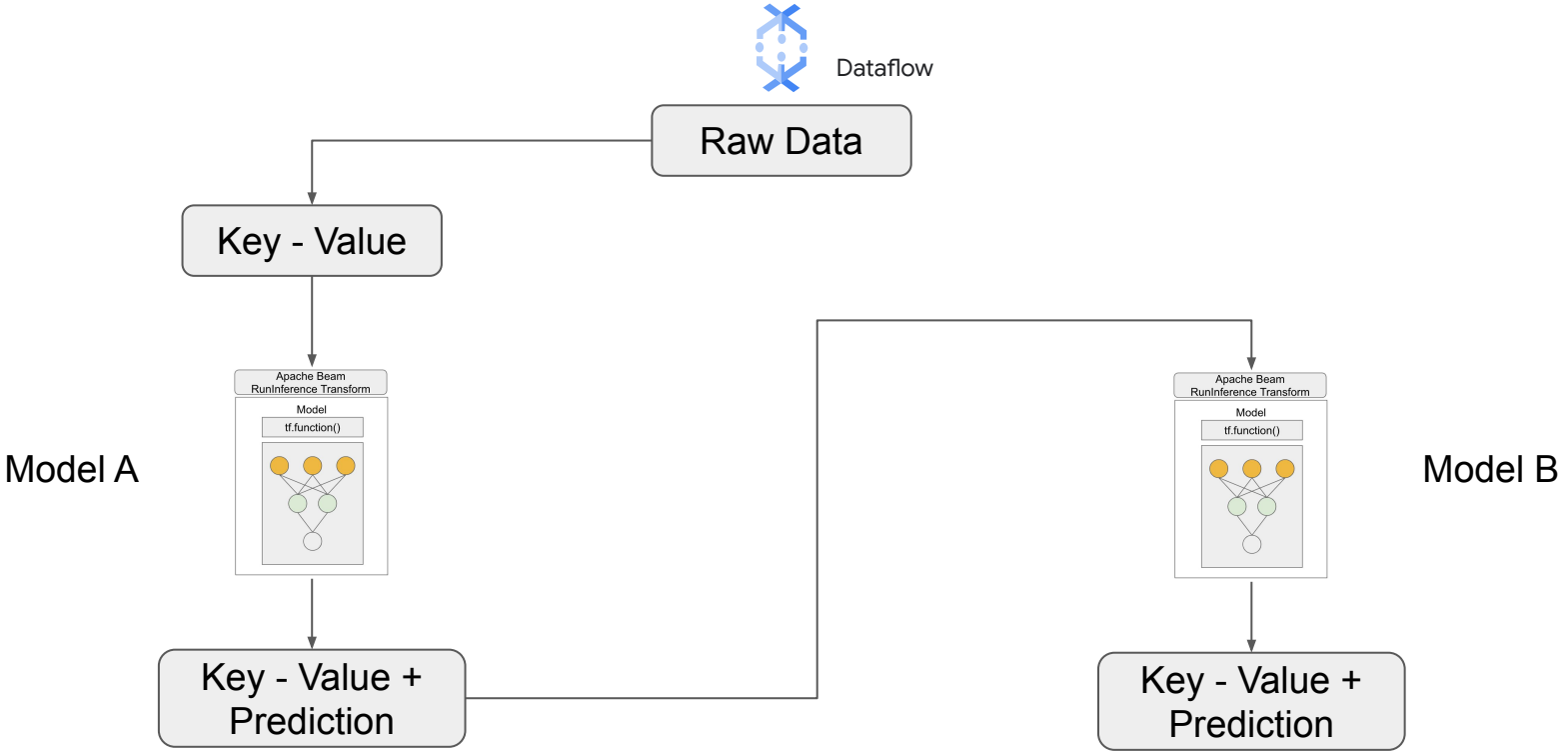


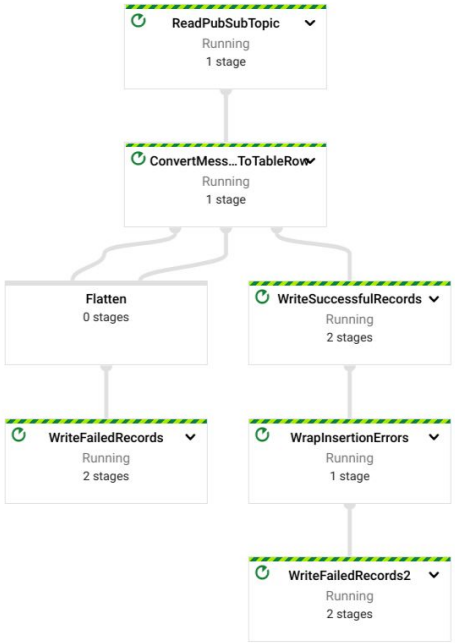
Sequential model



GPUs

Logical Pipeline View - The need for GPUs

- Execution graph created from code
- Use CPU for stages are more suited for CPU based processing
- Leverage GPU to accelerate specific stages of the pipeline

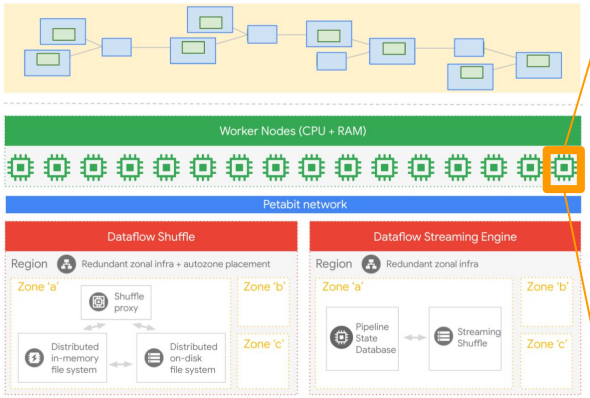


Dataflow GPU

Attach GPU to your Dataflow workers to accelerate your pipelines

- Select from a range of GPU types (NVIDIA T4, V100, P100, and P4) for your job. Up to 8 GPUs per instance
- Automatic provisioning/ deprovisioning
- Simplify application lifecycle with support for Docker containers

Dataflow GPU: Architecture View



Container Image
(SDK Worker Container)

User's Beam code
ML Framework (TensorFlow, Pytorch)
NVIDIA CUDA-X libraries
NVIDIA CUDA Toolkit
Apache Beam SDK

Dataflow Worker

GPU drivers
Dataflow Runner Process

Thank you!