RunInference: Machine Learning Inferences in Beam

By Andy Ye



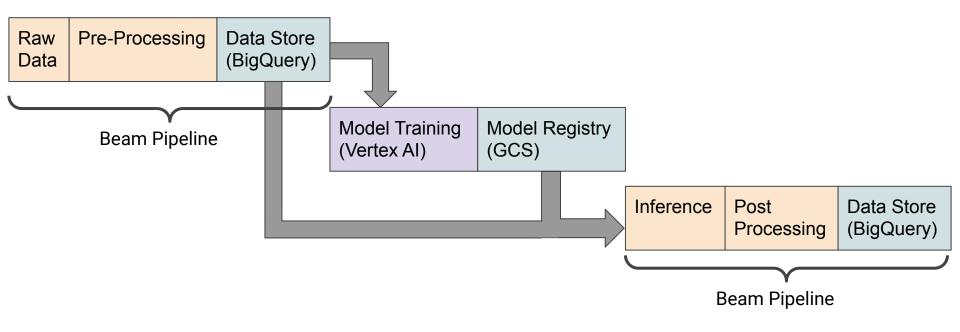
Agenda



- 1. Background: ML lifecycle, and previous limitations in Beam
- 2. RunInference: Machine learning inferences in Beam
- 3. RunInference API: Usage, patterns, and features
- 4. RunInference in the future
- 5. RunInference demo

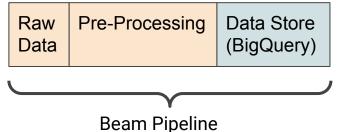
Typical Machine Learning Lifecycle





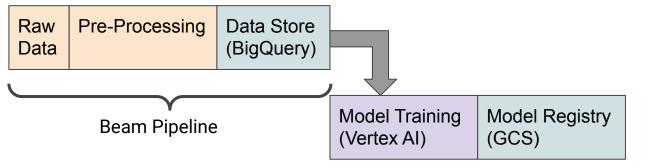






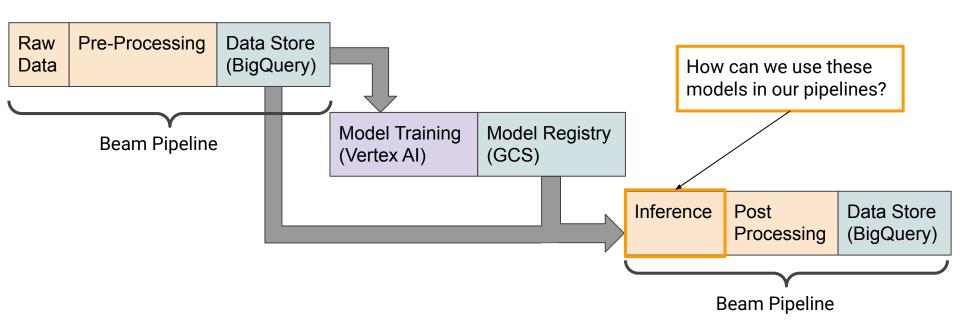






Typical Machine Learning Lifecycle









Most Machine Learning frameworks

TensorFlow

Users must write a custom DoFn

```
global_scale_setting = Floaters
def execute(self, context);
   folder_path = (os.path.dirname(self.filepath))
   viewport_selection = bpy.context.selected_objects
   obj_export_list = viewport_selection
   if self.use selection setting == False:
       obj_export_list = [i for i in bpy.context.scene.objects]
  bpv.ops.object.select_all(action='DESELECT')
  for item in obj_export_list:
      item.select = True
          os.path.join(folder_path, "{}.obj".format(item.name))
          xport_scene.obj(filepath=file_path, use_selection=frue,
                                  axis_forward=self.axis_forward_setting,
                                   axis up=self.axis_up_setting,
                                               fiers=self.use_mesh_modifiers_setting,
```

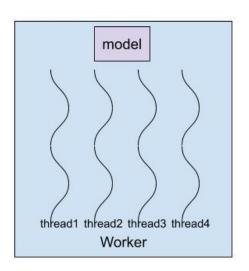
Users use RunInference from the *tfx_bsl* utility



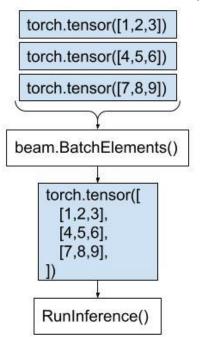
RunInference: A new Beam transform to run ML inferences



Shared class



Dynamic Batching



- Key forwarding
- Processing the output
- Standard Metrics
- GPUs

Supported Frameworks









^{*} TF support via the tensorflow/tfx-bsl repo. A migration to Beam is anticipated soon.

How to use RunInference



ModelHandlers



```
from apache beam.ml.inference.sklearn inference import SklearnModelHandlerNumpy
from apache beam.ml.inference.sklearn inference import SklearnModelHandlerPandas
from apache beam.ml.inference.pytorch inference import PytorchModelHandlerTensor
from apache beam.ml.inference.pytorch inference import PytorchModelHandlerKeyedTensor
model handler = SklearnModelHandlerNumpy(model uri='model.pkl',
                                         model file type=ModelFileType.JOBLIB)
model handler = PytorchModelHandlerTensor(state dict path='linear regression.pth',
                                          model class=PytorchLinearRegression,
                                          model params={'input dim': 1, 'output dim': 1})
```

KeyedModelHandler



```
from apache beam.ml.inference.base import KeyedModelHandler
keyed model handler = \
   KeyedModelHandler(PytorchModelHandlerTensor(...))
with pipeline as p:
   data = p | beam.Create([
      ('img1', np.array[[1,2,3],[4,5,6],...]),
      ('img2', np.array[[1,2,3],[4,5,6],...]),
      ('img3', np.array[[1,2,3],[4,5,6],...]),
   1)
   predictions = data | RunInference(keyed model handler)
```

Creating Ensembles



- A/B Pattern
- Sequential Pattern

A/B Pattern



```
with pipeline as p:
    data = p | 'Read' >> beam.ReadFromSource('a_source')
    model_a_predictions = data | RunInference(ModelHandlerA)
    model_b_predictions = data | RunInference(ModelHandlerB)
```

Sequential Pattern



```
with pipeline as p:
    data = p | 'Read' >> beam.ReadFromSource('a_source')
    model_a_predictions = data | RunInference(ModelHandlerA)
    model_b_predictions = (
        model a predictions | RunInference(ModelHandlerB))
```

PredictionResult



```
class PostProcessor(beam.DoFn):
    def process(self, element: Tuple[str, PredictionResult]):
       key, prediction result = element
       inputs = prediction result.example
       predictions = prediction result.inference
       # Post-processing logic
       result = ...
       yield (key, result)
with pipeline as p:
    output = (
        p | 'Read' >> beam.ReadFromSource('a source')
            'PytorchRunInference' >> RunInference(KeyedModelHandler)
            'ProcessOutput' >> beam.ParDo(PostProcessor()))
```

Metrics



- Namespaces
- num_inferences
- Count, min, max, mean of
 - batch_size
 - msec_per_batch
 - inference_batch_latency_micro_secs
 - inference_request_batch_byte_size
 - inference_request_batch_size
 - load_model_latency_milli_secs
 - model_byte_size

Metrics in the UI of a Dataflow job

Custom counters

| ∓ Filter mean ③ Filter by counter name | ne, value or step | |
|--|-------------------|------------------------|
| Counter name | Value | Step |
| batch_size_MEAN | 1 | PyTorch RunInference// |
| msec_per_batch_MEAN | 14,146 | PyTorch RunInference// |
| inference_batch_latency_micro_secs_MEAN | 13,625,472 | PyTorch RunInference// |
| inference_request_batch_byte_size_MEAN | 16 | PyTorch RunInference// |
| inference_request_batch_size_MEAN | 1 | PyTorch RunInference// |
| load_model_latency_milli_secs_MEAN | 6,347 | PyTorch RunInference// |
| model_byte_size_MEAN | 402,484,199 | PyTorch RunInference// |
| | | |

RunInference in the future



- Optional batching
- Streaming with side inputs
- Integration with remote services (e.g. Vertex AI)

More frameworks! Please help contribute!



And more!

Related Links



- Machine Learning in Beam https://beam.apache.org/documentation/sdks/python-machine-learning/
- RunInference Transform
 https://beam.apache.org/documentation/transforms/python/elementwise/runinference/
- Pipeline Examples
 https://github.com/apache/beam/tree/master/sdks/python/apache_beam/examples/inference
- RunInference Python Documentation
 https://beam.apache.org/releases/pydoc/current/apache_beam.ml.inference

 .html#apache_beam.ml.inference.RunInference

Thank you!



Demo time!