Inference at Scale with Apache Beam

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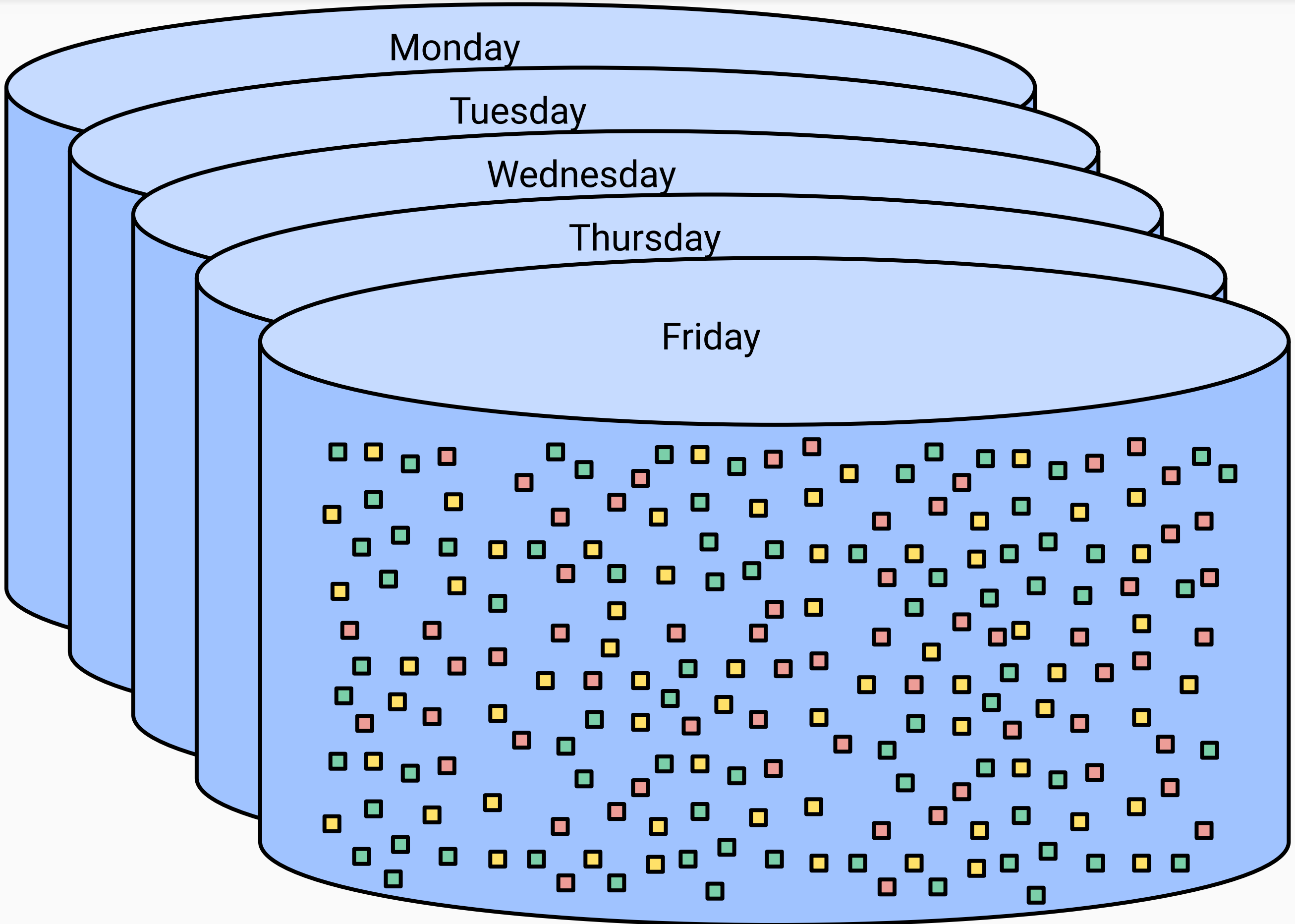
docs.google.com/presentation/d/1JJiLxXEPJgxspDsVpWvnccaGQU2o3xVYPRdZZ6OmWpE
(or shorturl.at/qxZ38)

Topics

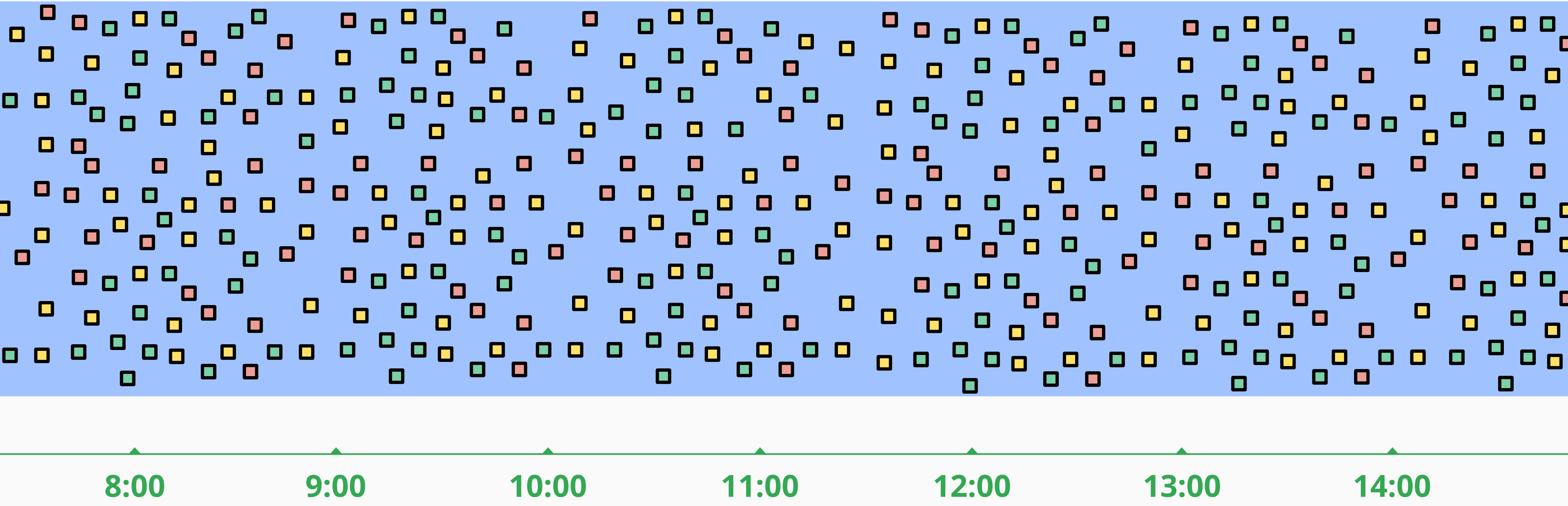
1. Beam History + Overview
2. Basic Inference
3. Problems/Solutions
   - Model Freshness
   - Large Models
   - Specialty Hardware
4. Where Next?

What is Apache Beam

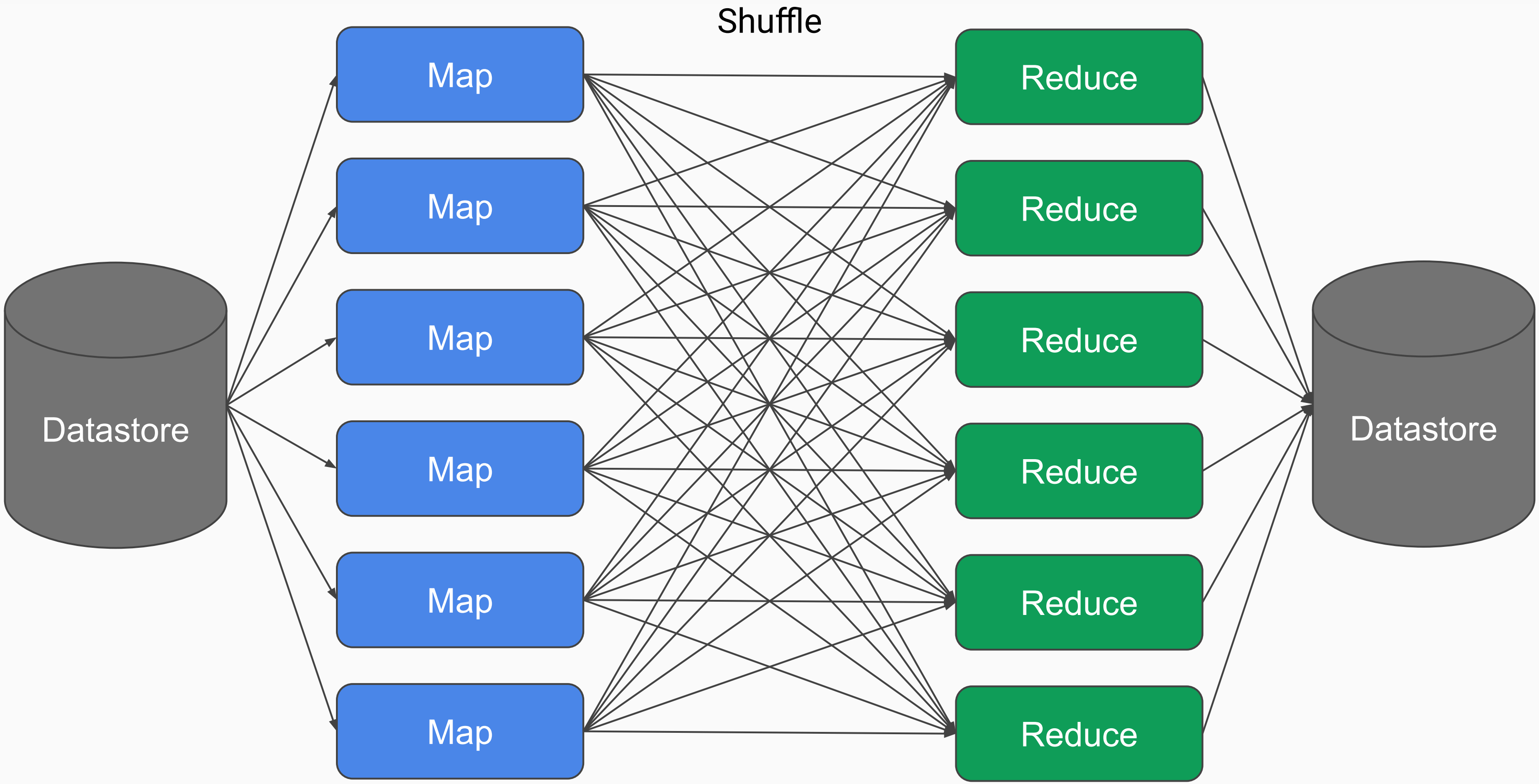
Data got big:



And neverending!



In the beginning, there was MapReduce



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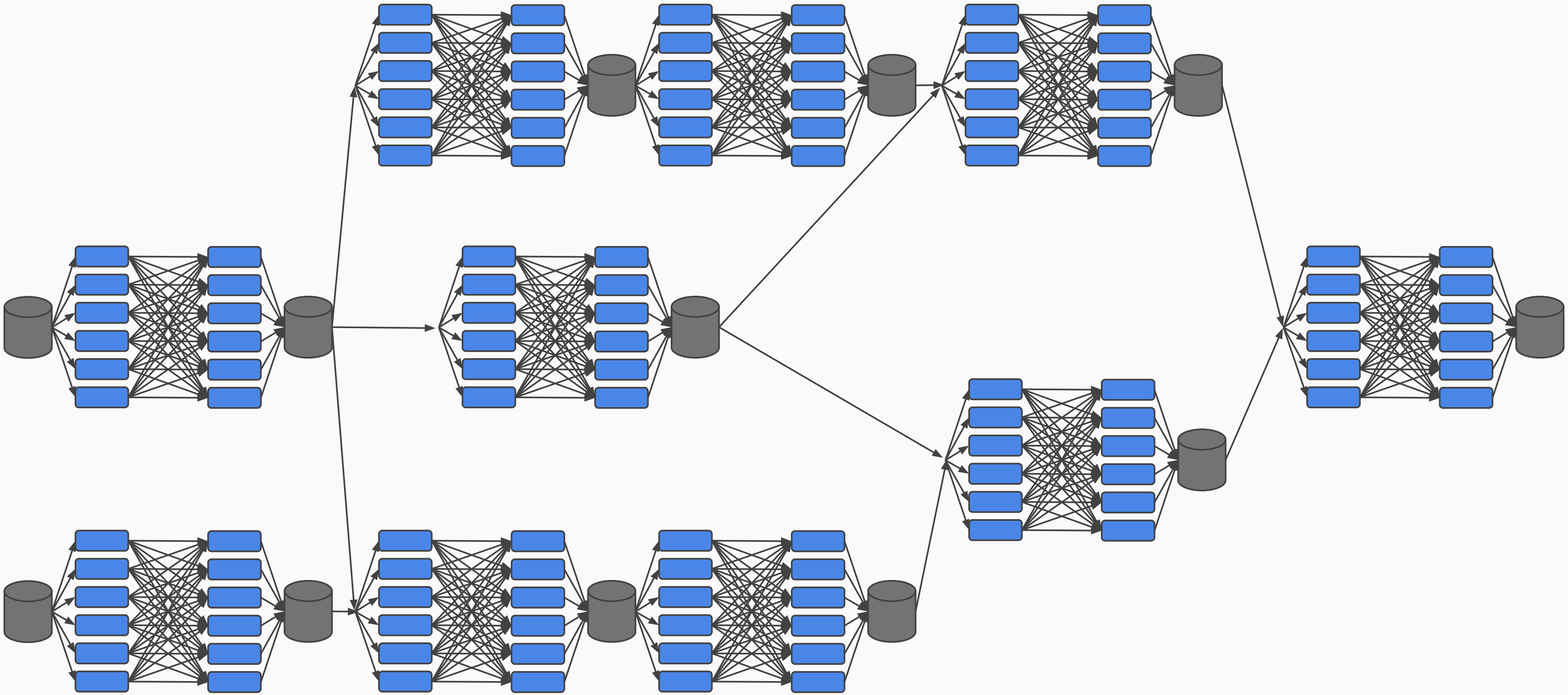
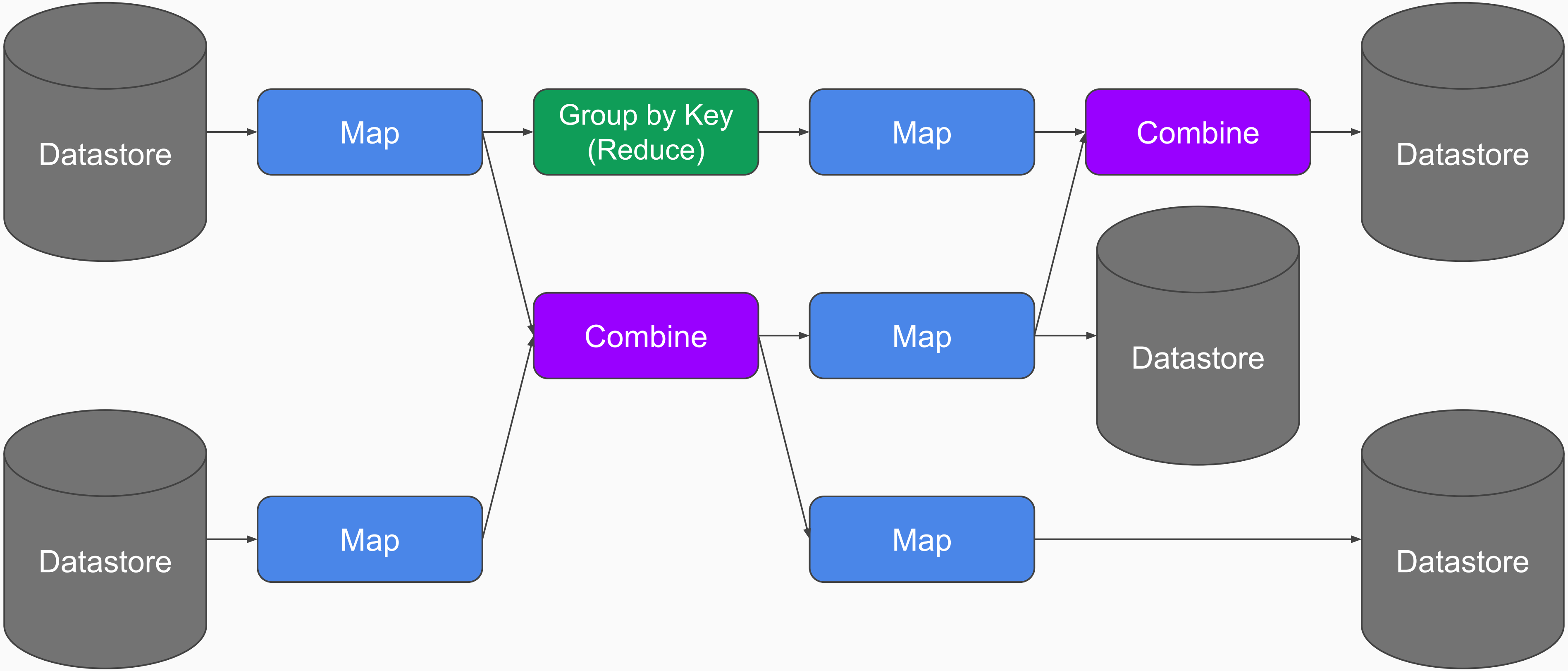
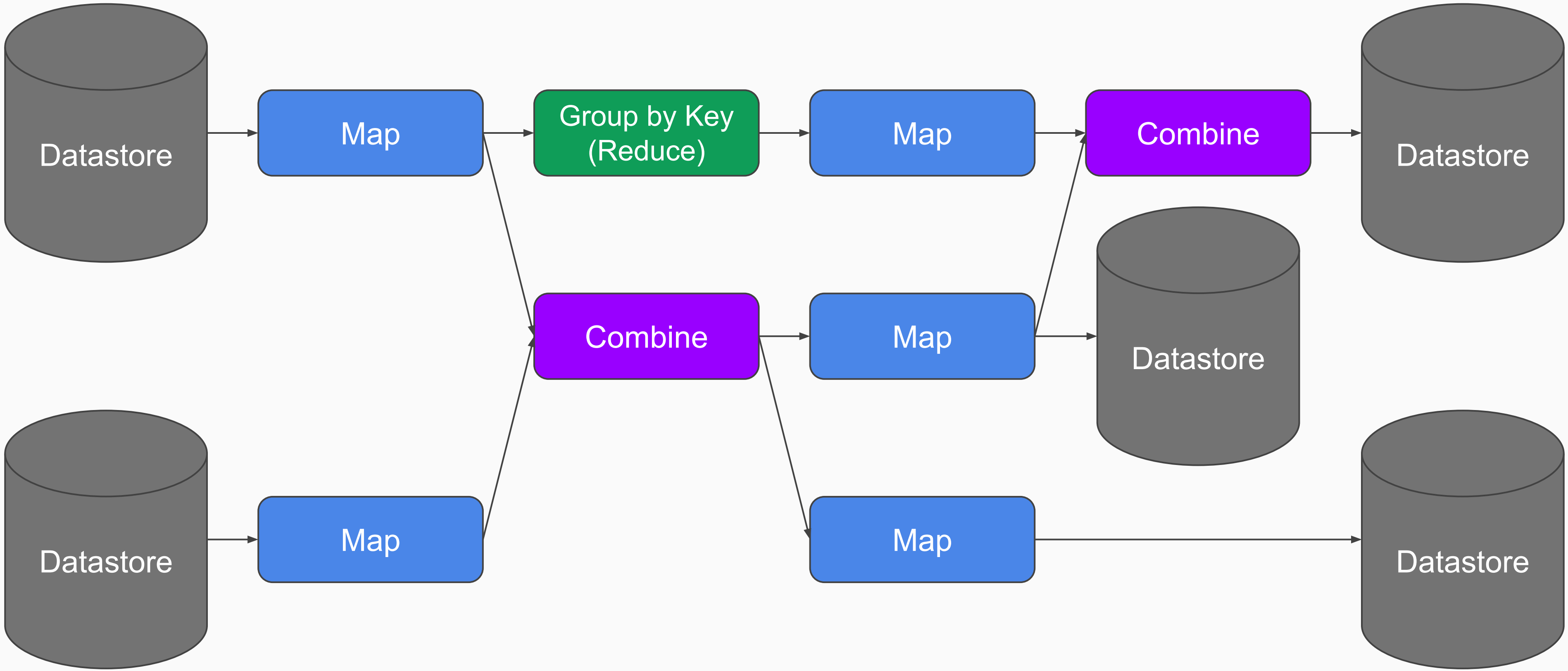


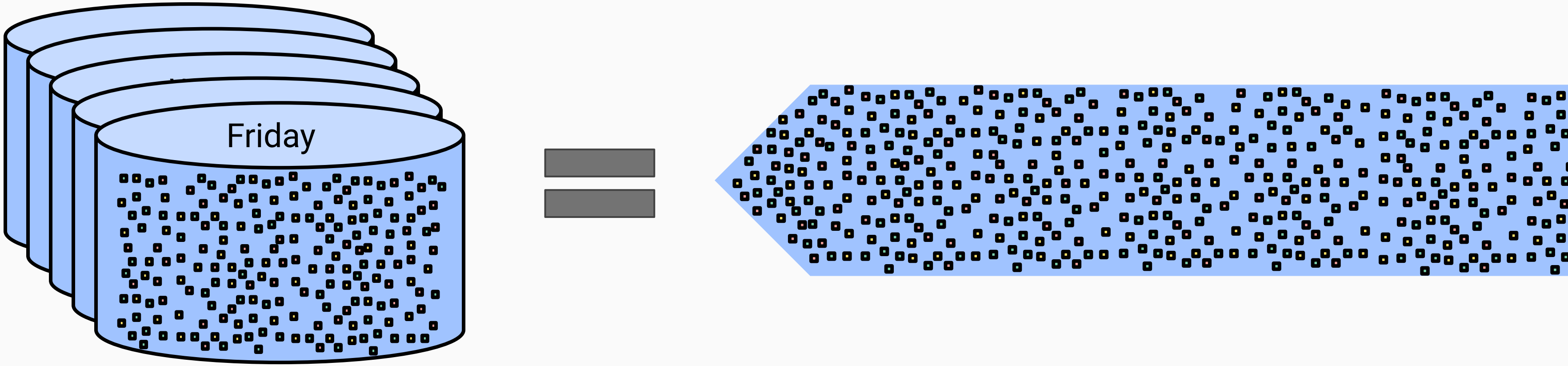
Then came Flume



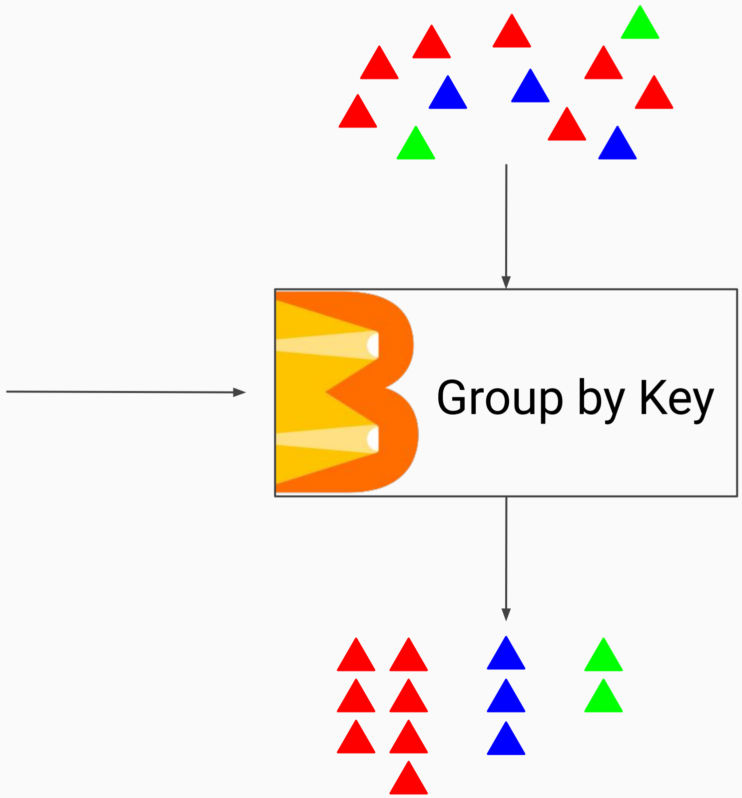
From Flume came Beam



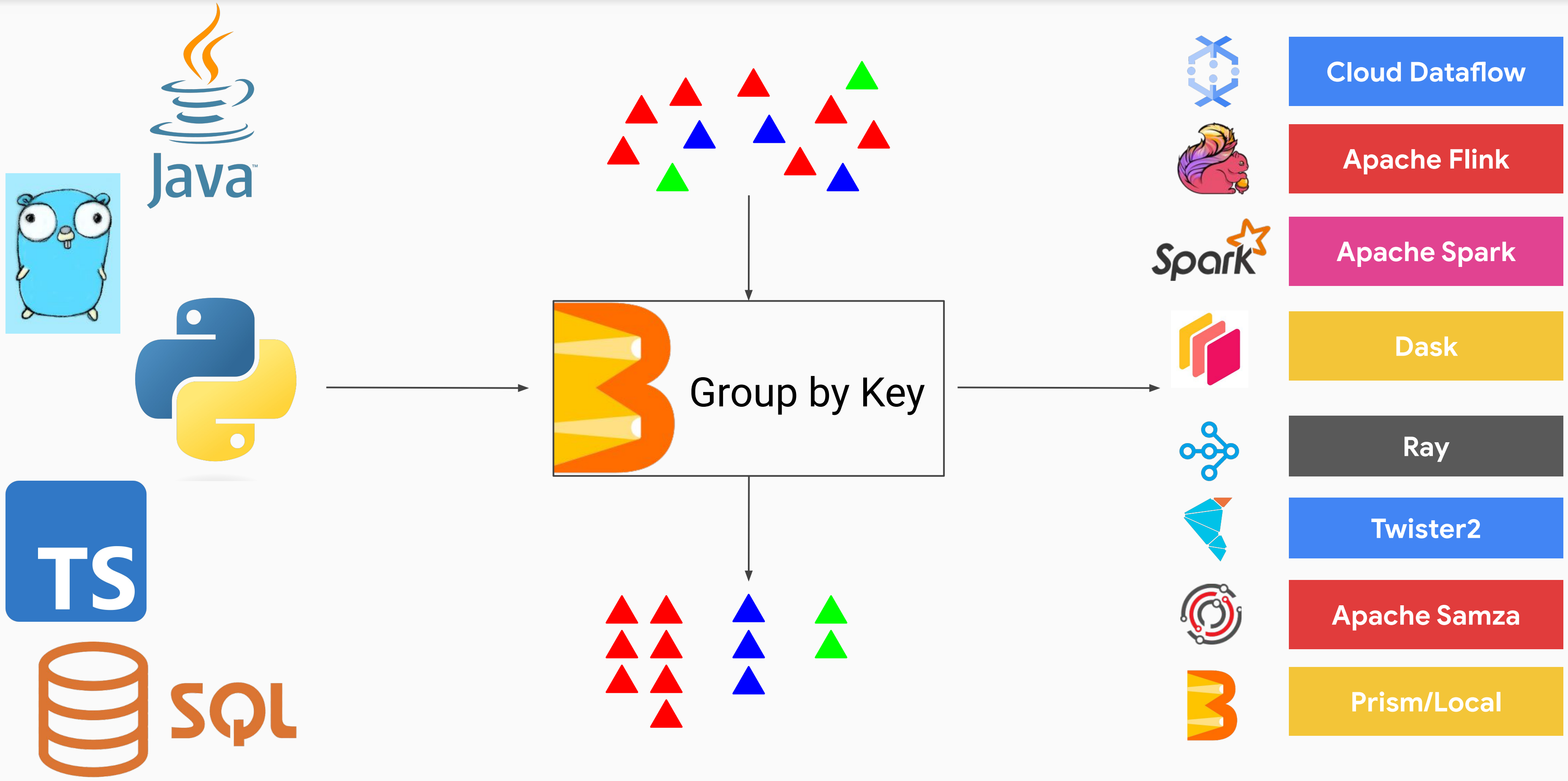
- Batch processing is a special case of stream processing
- Batch + Stream = Beam



Build your pipeline in whatever language(s) you want…



… with whatever execution engine you want

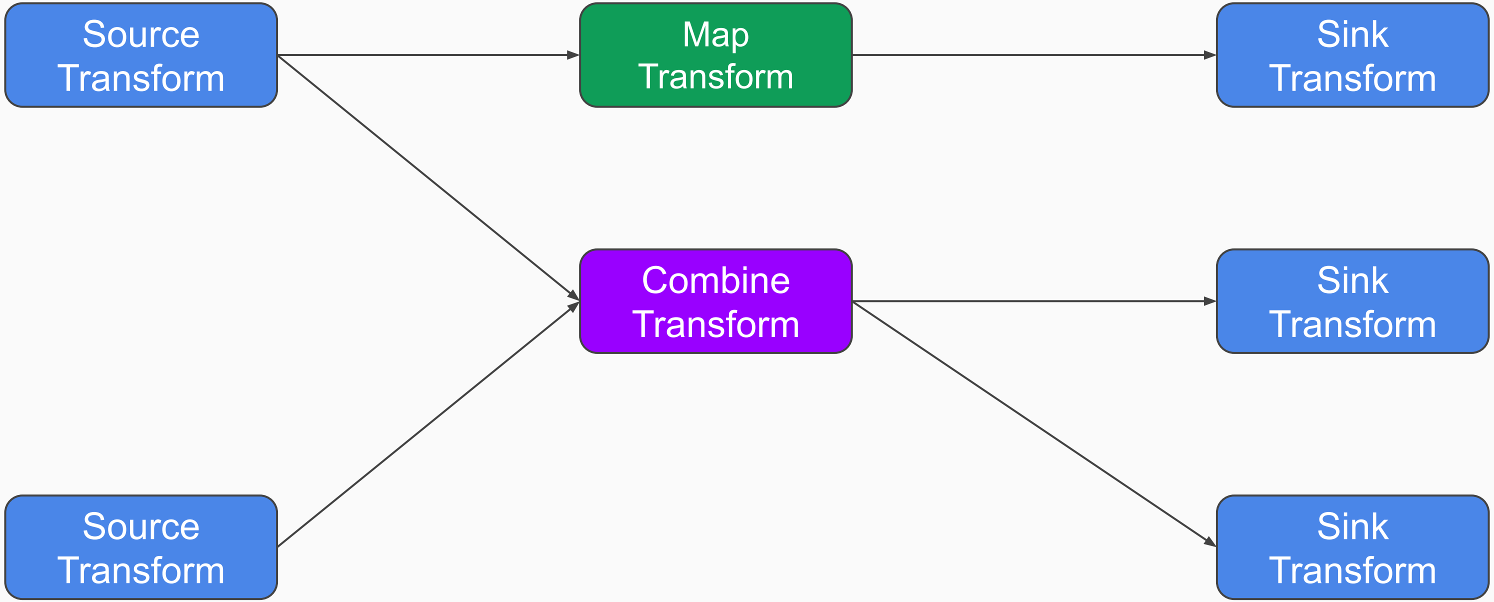


Beam Basics

Terms

- **PCollection** - distributed multi-element dataset
- **Transform** - operation that takes N PCollections and produces M PCollections
- **Pipeline** - directed acyclic graph of **Transforms** and **PCollections**

Basic Beam Graph

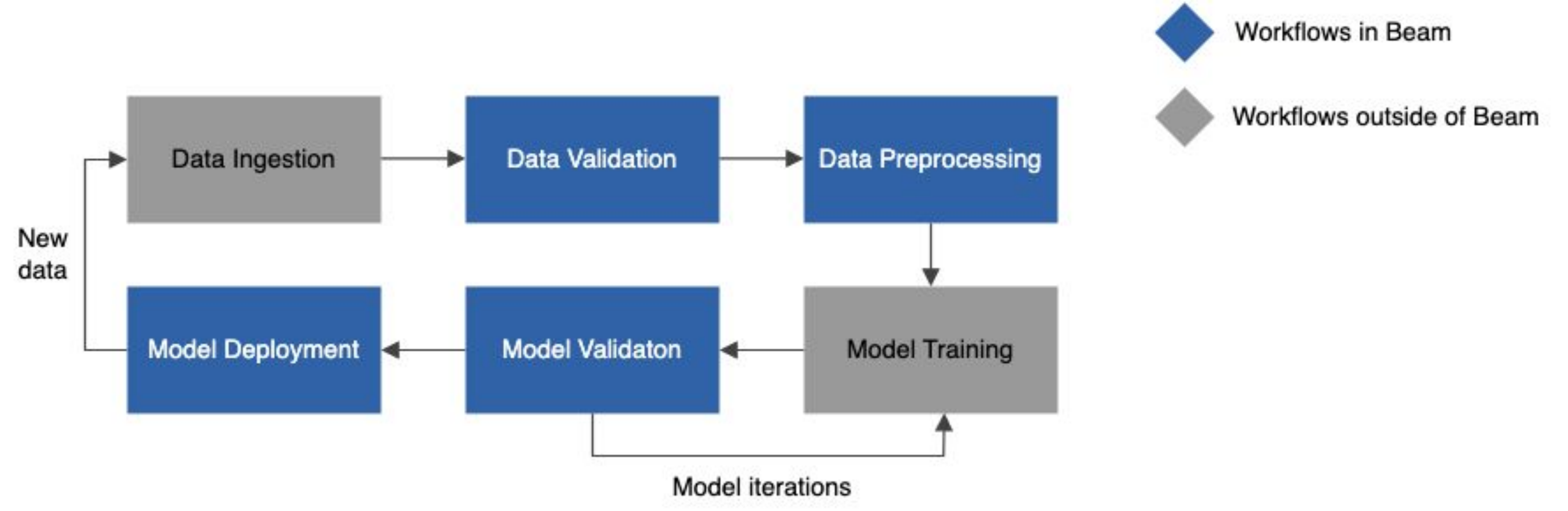


Basic Beam Pipeline

```python
def add_one(element):
     return element + 1

import apache_beam as beam
with beam.Pipeline() as pipeline:
     pipeline
     | beam.io.ReadFromText('gs://some/inputData.txt')
     | beam.Map(add_one)
     | beam.io.WriteToText('gs://some/outputData')
```

Beam ML

The ML lifecycle



Inference with Beam

Challenges of Distributed Inference

- Efficiently loading models
- Batching
- Model Updates
- Using multiple models

- Beam takes care of all of this with the RunInference transform
- Loads model, batches inputs, handles updates, and plugs into DAG

```
RunInference(model_handler=<config>)
```

RunInference

```
>>> data = numpy.array([10, 40, 60, 90],
...                            dtype=numpy.float32).reshape(-1, 1)

>>> model_handler = PytorchModelHandlerTensor(
...    model_class=LinearRegression,
...    model_params={'input_dim': 1, 'output_dim': 1},
...    state_dict_path='gs://path/to/model.pt')

>>> with beam.Pipeline() as p:
...   predictions = (
...       p
...       | beam.Create(data)
...       | beam.Map(torch.Tensor) # Map np array to Tensor
...       | RunInference(model_handler=model_handler)
...       | beam.Map(print))
```

Basic Inference Demo

colab.sandbox.google.com/github/apache/beam/blob/master/examples/notebooks/beam-ml/run_inference_huggingface.ipynb
(shorturl.at/brvN9)

Automatic Model Refresh

You’ve deployed your model! Now what?

- New data
- New training algorithms
- New models

Options

- Stop and start your pipeline
- Pipeline drain/update
- Automatic model refresh

Automatic Model Refresh

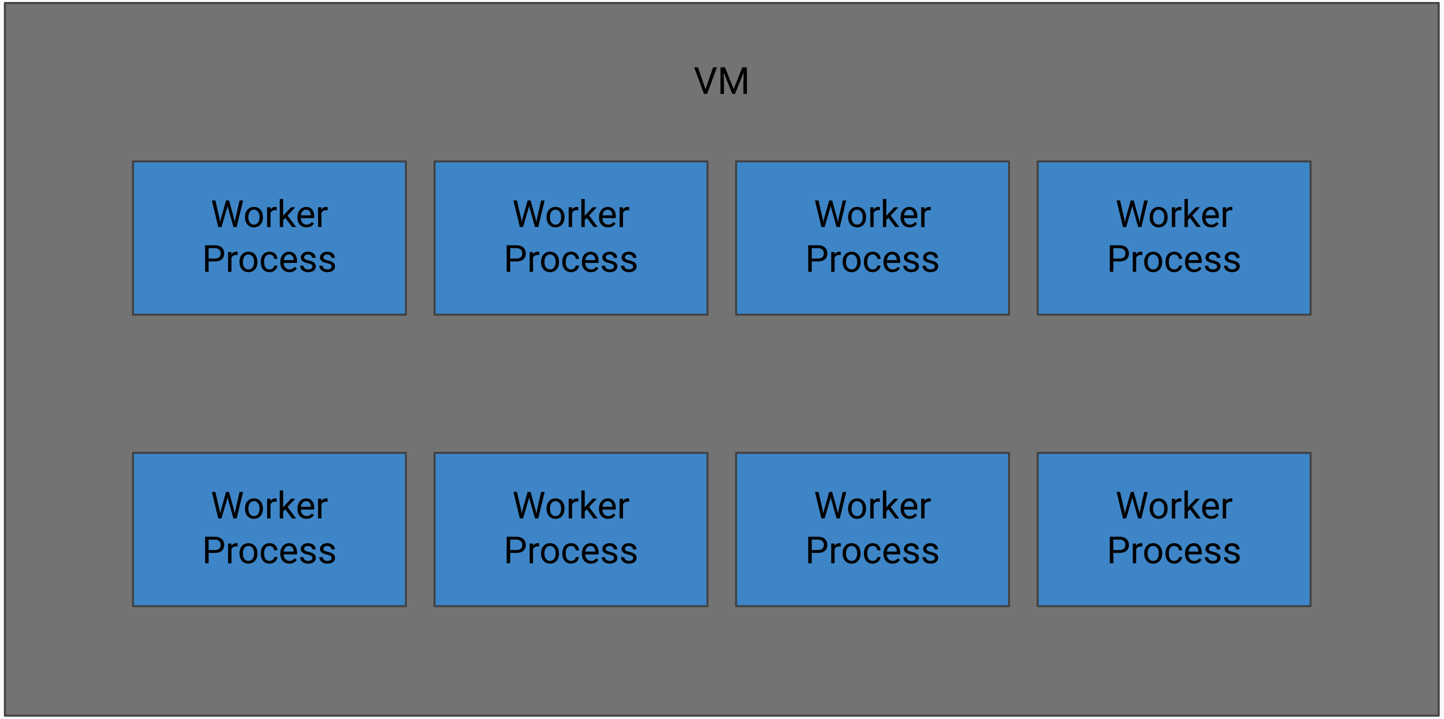
- Hot swaps model in live pipeline
- Manages memory for you
- No pipeline down time (though maybe some inference down time)

Automatic Model Refresh

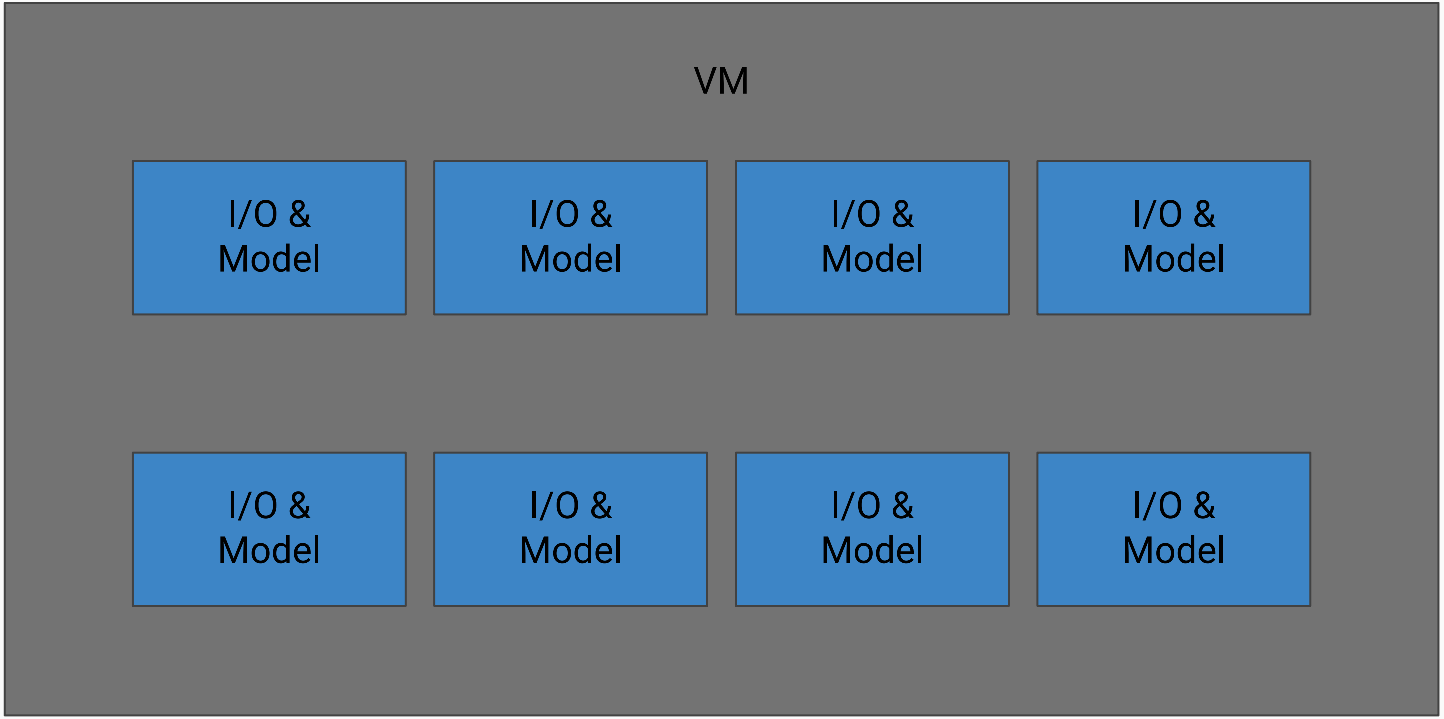
```
side_input_pcoll = (pipeline
| "WatchFilePattern" >> WatchFilePattern(file_pattern=file_pattern,
interval=side_input_fire_interval,
stop_timestamp=end_timestamp))

inferences = (image_data
| "ApplyWindowing" >> beam.WindowInto(beam.window.FixedWindows(10))
| "RunInference" >> RunInference(model_handler=model_handler,
model_metadata_pcoll=side_input_pcoll))
```

Large Models

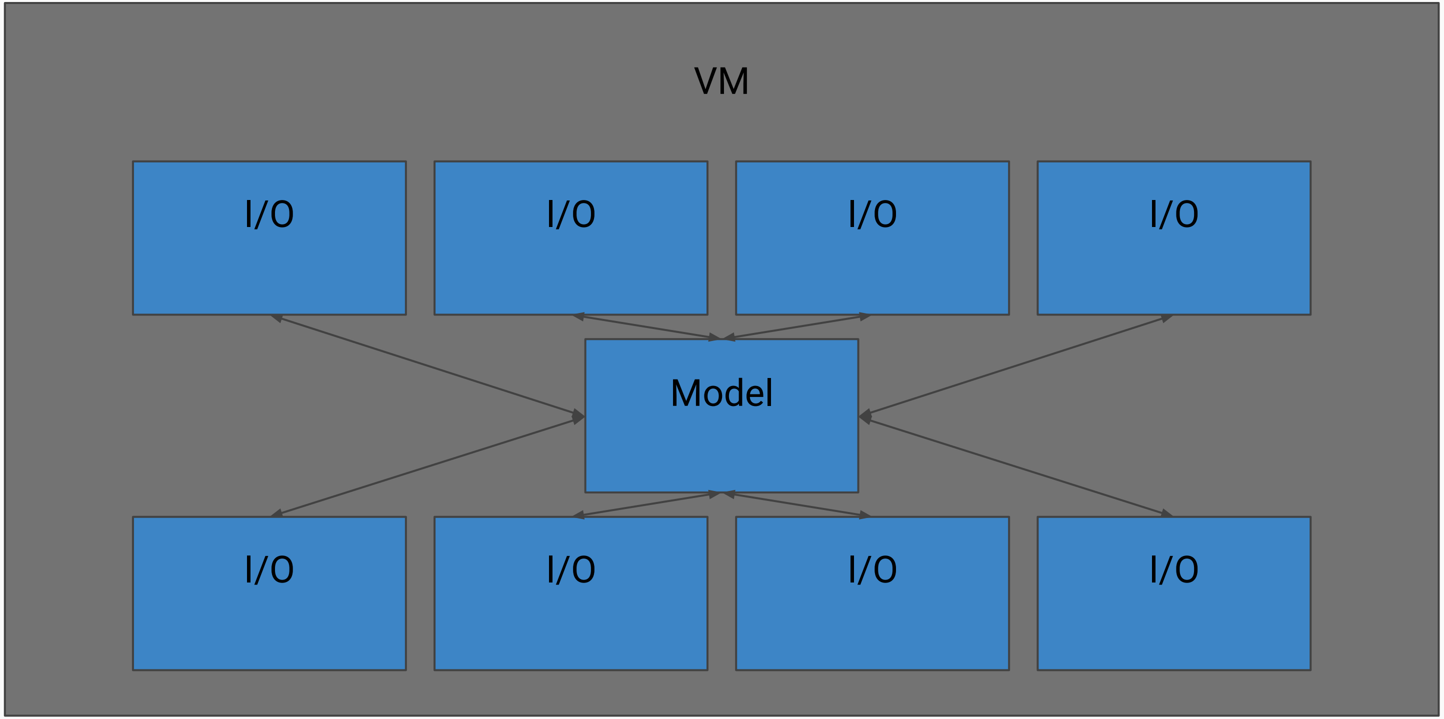
Distributed Runner Architecture*



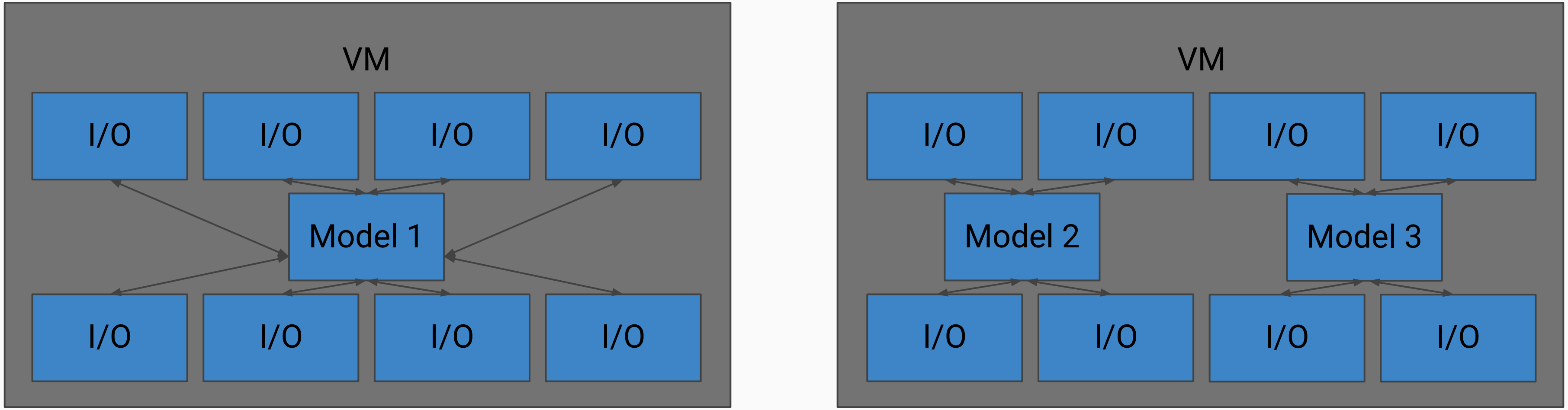
Ideal small model configuration



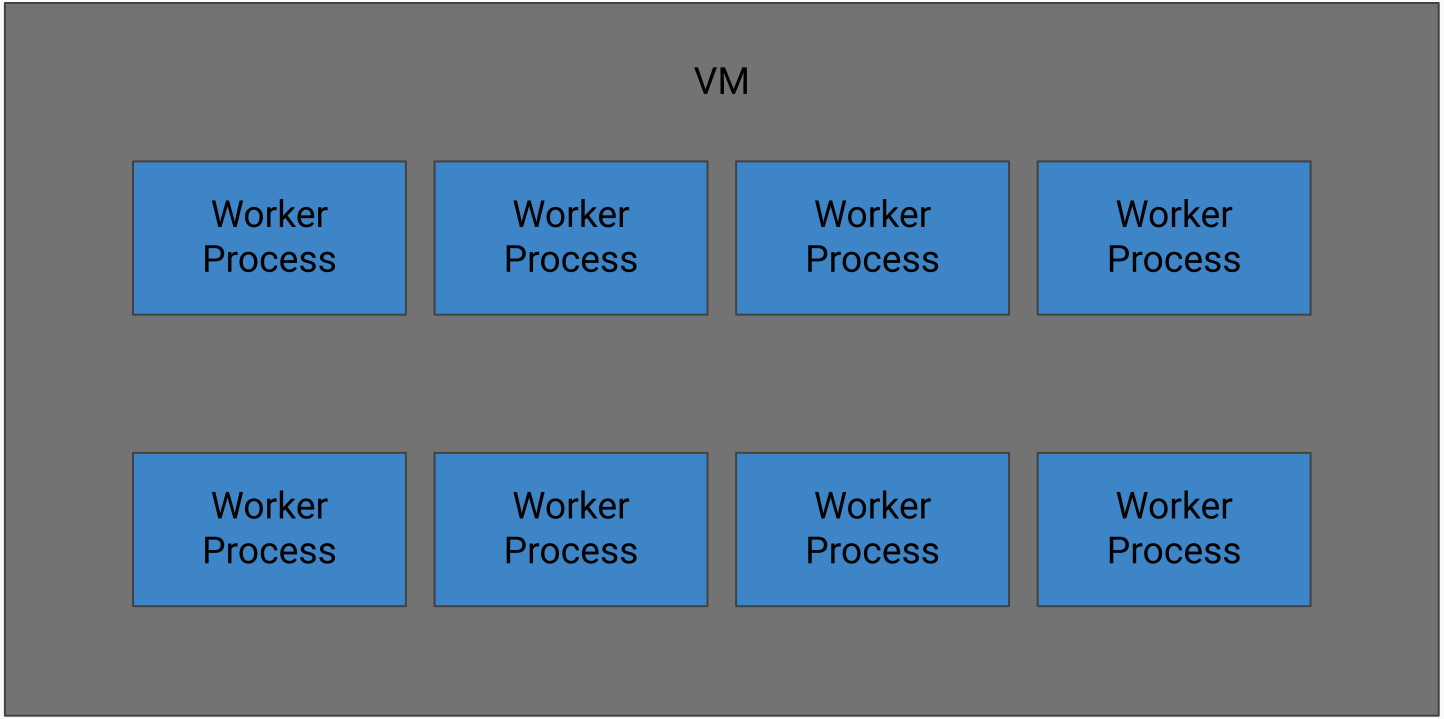
Ideal Large Model Configuration



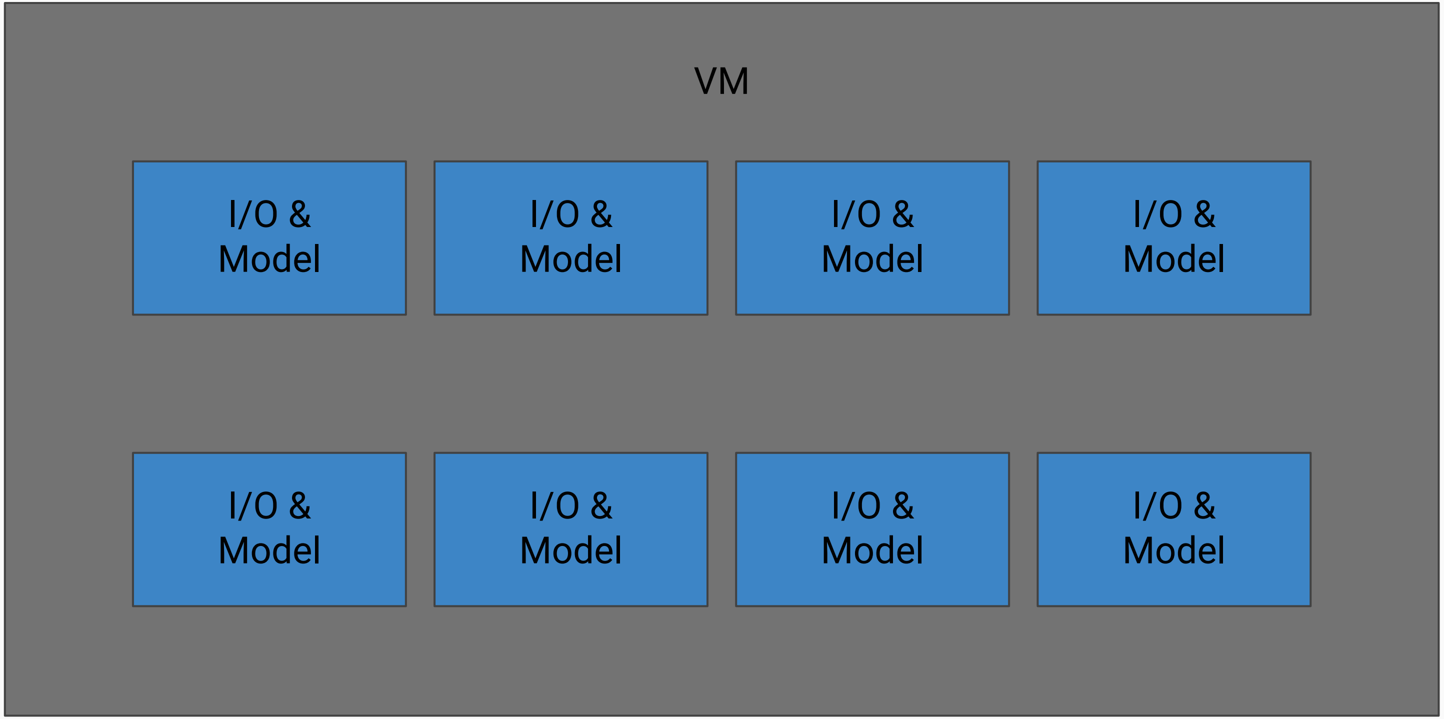
Ideal Multi Large Model Configuration



How do we map ideal model configurations to this?



Ideal small model configuration

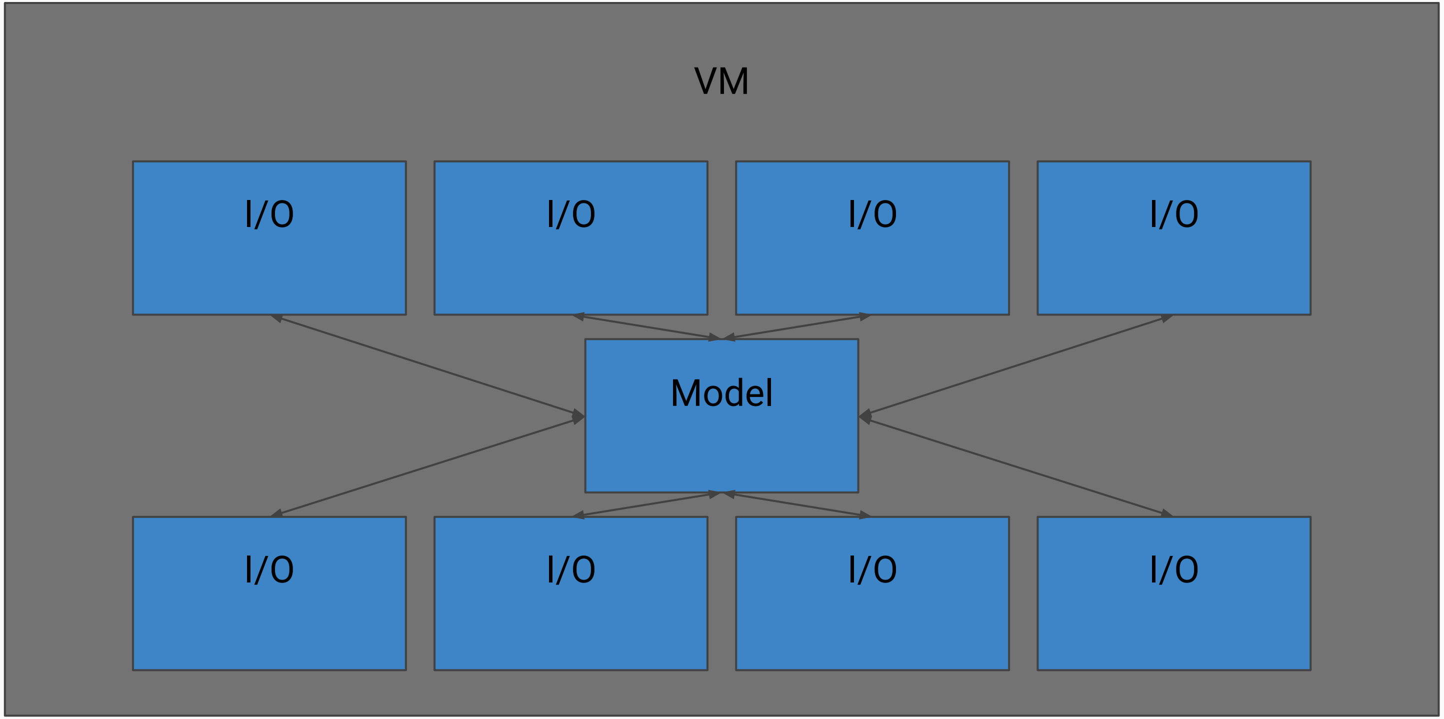


Default configuration: share model across threads

- Aka the easy case

```
>>> model_handler = PytorchModelHandlerTensor(
...     model_class=LinearRegression,
...     model_params={'input_dim': 1, 'output_dim': 1},
...     state_dict_path='gs://path/to/model.pt')

>>> pcoll | RunInference(model_handler=model_handler)
```

Ideal Large Model Configuration



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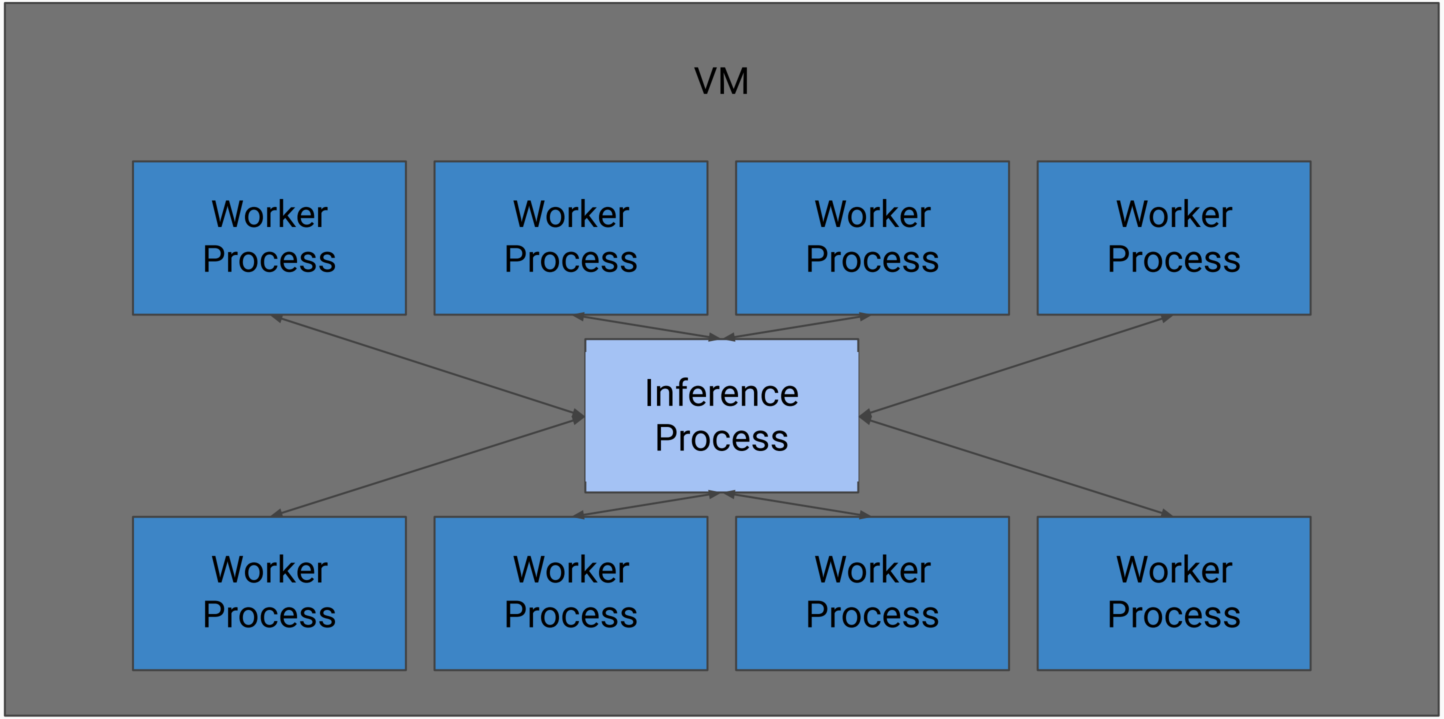


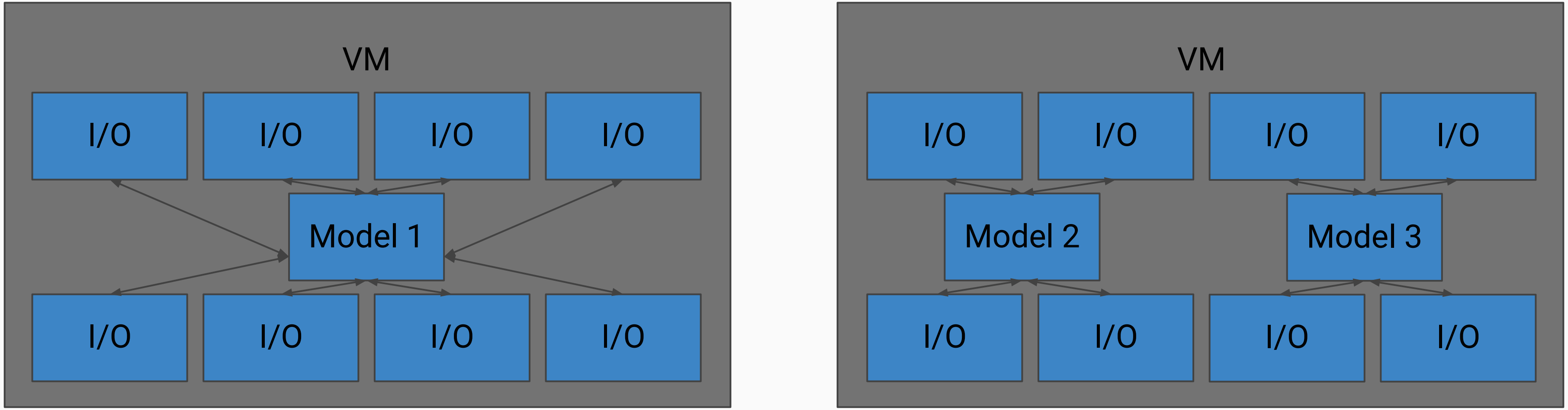
Optional: serve a single model for all processes

- Reduce memory at cost of interprocess communication, minimized parallelism

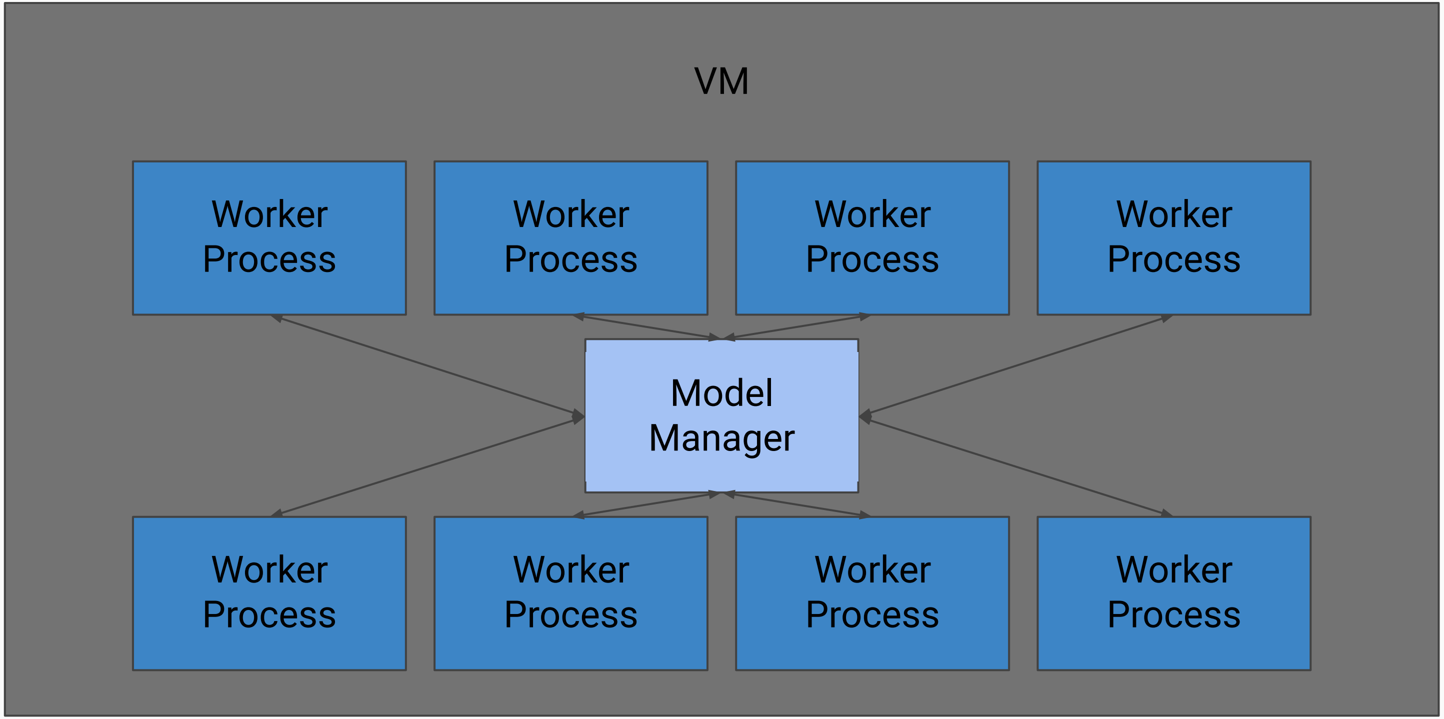
```
>>> model_handler = PytorchModelHandlerTensor(
...     model_class=LinearRegression,
...     large_model=True,
...     model_params={'input_dim': 1, 'output_dim': 1},
...     state_dict_path='gs://path/to/model.pt')

>>> pcoll | RunInference(model_handler=model_handler)
```

Ideal Multi Large Model Configuration



Ideal Large Model Configuration



Optional: serve a single model for all processes

- Model Manager empowered to load/unload models in order to make optimal use of memory

```
>>> per_key_mhs = [
...   KeyModelMapping(['key1', 'key2', 'key3'], model_handler_1),
...   KeyModelMapping(['foo', 'bar', 'baz'], model_handler_2)]
>>> mh = KeyedModelHandler(per_key_mhs)

>>> pcoll | RunInference(model_handler=mh)
```

Large Model Demo

colab.sandbox.google.com/github/apache/beam/blob/master/examples/notebooks/beam-ml/per_key_models.ipynb
(shorturl.at/pKNU2)

Specialty Hardware

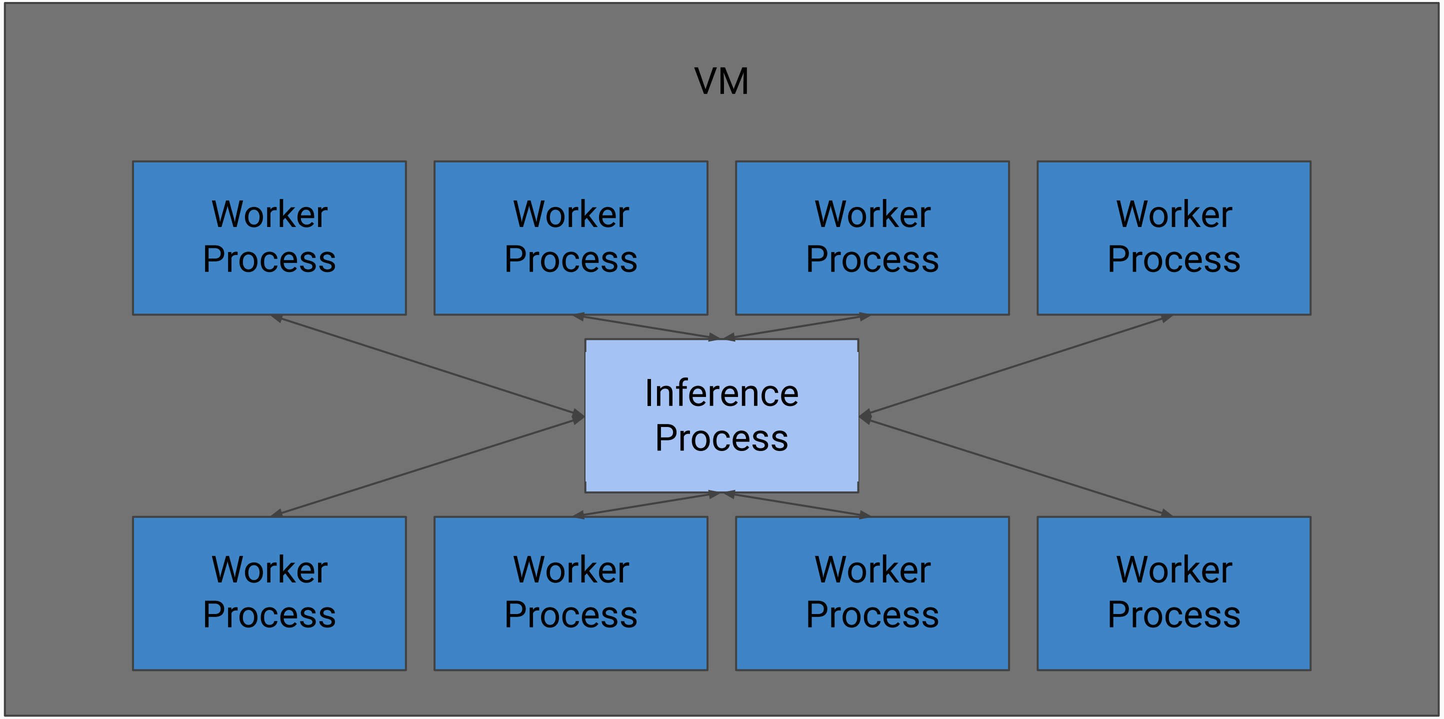
GPU/TPU Support

- Hardware availability dependent on runner
- Beam has some primitives that help

Beam Primitives for GPUs

- Resource hints for heterogeneous pools
- Built in detection + framework specific responses to GPUs at the ModelHandler level
- Large model setting (revisited)

Ideal Large Model Configuration



Where next?

(opportunities I see, not representative of the whole community)

Inference Space

- More frameworks
- Better performance testing/profiling
- Model Manager Improvements

Beyond Inference

- MLTransform for data prep and pre/postprocessing
- Feature Store Enrichment
- Higher level ML support (e.g. anomaly detection)

Come join our community!

Questions?

Contact - Danny McCormick (dannymccormick@google.com)

Slides - https://shorturl.at/jzEQ6