



Dataflows for machine learning operations

Andrei Paleyes and Alex Rakowski



Part I – Dataflow and Streams

What is ML@CL group?

Machine
Learning
@
Computer
Lab



ML@CL



UNIVERSITY OF
CAMBRIDGE

Dataflow research at ML@CL

Towards better data discovery and collection with flow-based programming

RESEARCH-ARTICLE OPEN ACCESS

Causal fault localisation in dataflow systems

Christian Cabrera

Authors: Andrei Paleyes, Neil David Lawrence [Authors Info & Claims](#)

EuroMLSys '23: Proceedings of the 3rd Workshop on Machine Learning and System
140–147 • <https://doi.org/10.1145/3578356.3592593>

RESEARCH-ARTICLE OPEN ACCESS

An empirical evaluation of flow based programming in the machine learning deployment context

Authors:  Andrei Paleyes,  Christian Cabrera,  Neil D. Lawrence [Authors Info & Claims](#)

CAIN '22: Proceedings of the 1st International Conference on AI Engineering: Software Engineering for AI • May 2022 • Pages

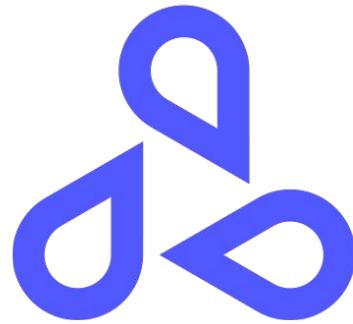
Dataflow graphs as complete causal graphs

Andrei Paleyes^{*1}, Siyuan Guo^{*12}, Bernhard Schölkopf², Neil D. Lawrence¹

¹*Department of Computer Science and Technology, University of Cambridge*

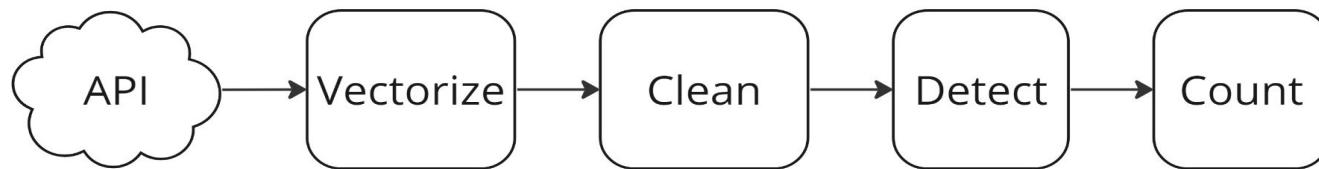
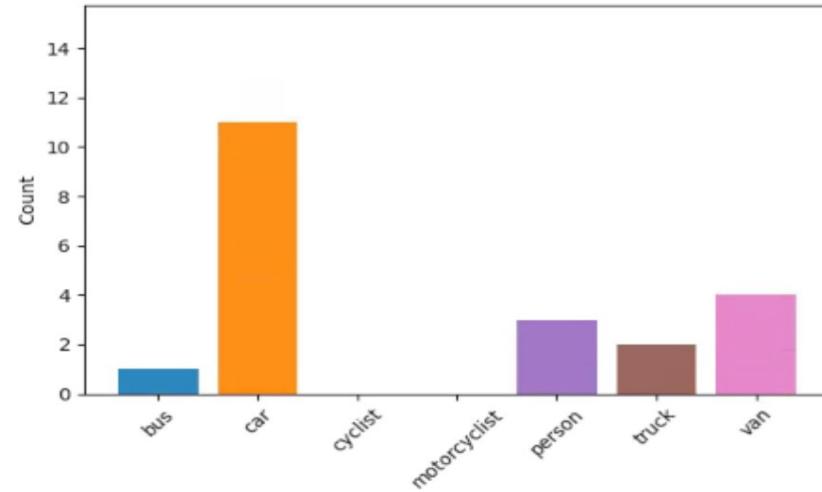
²*Max Planck Institute for Intelligent Systems*

Open Source: Seldon Core



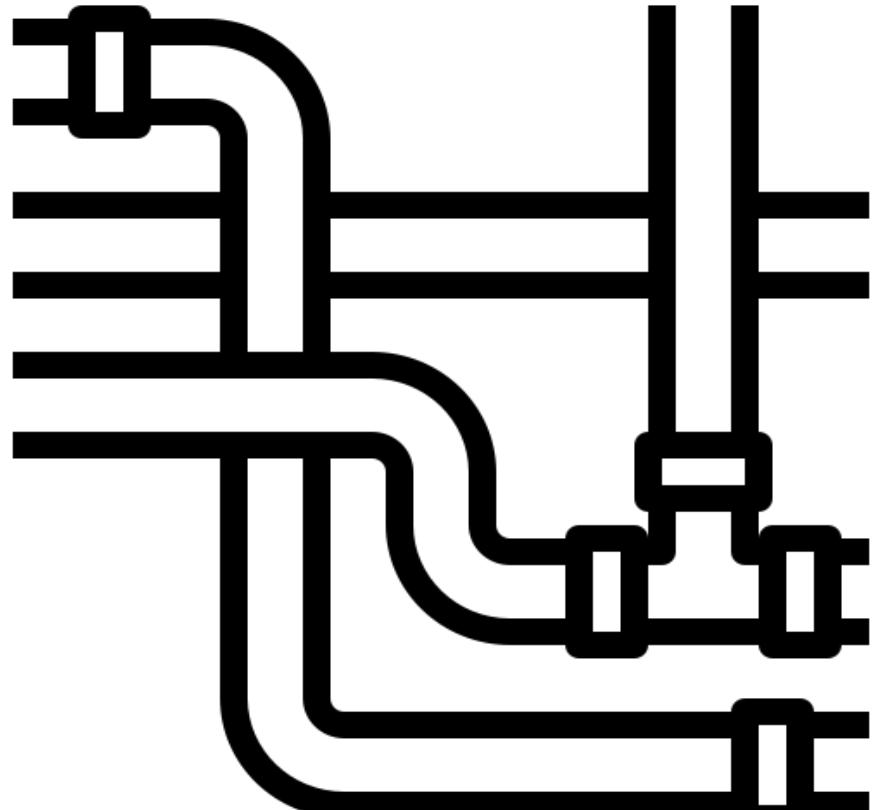
SELDON
CORE

Inference graph

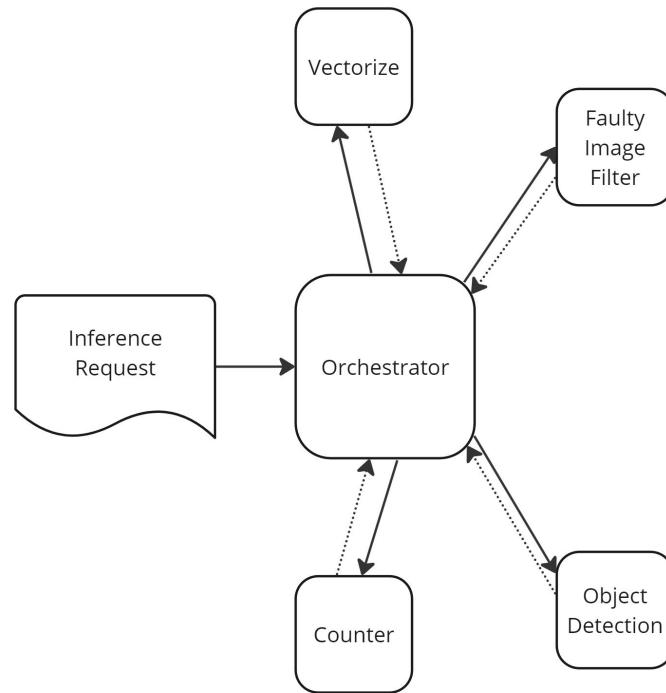


Pipelines

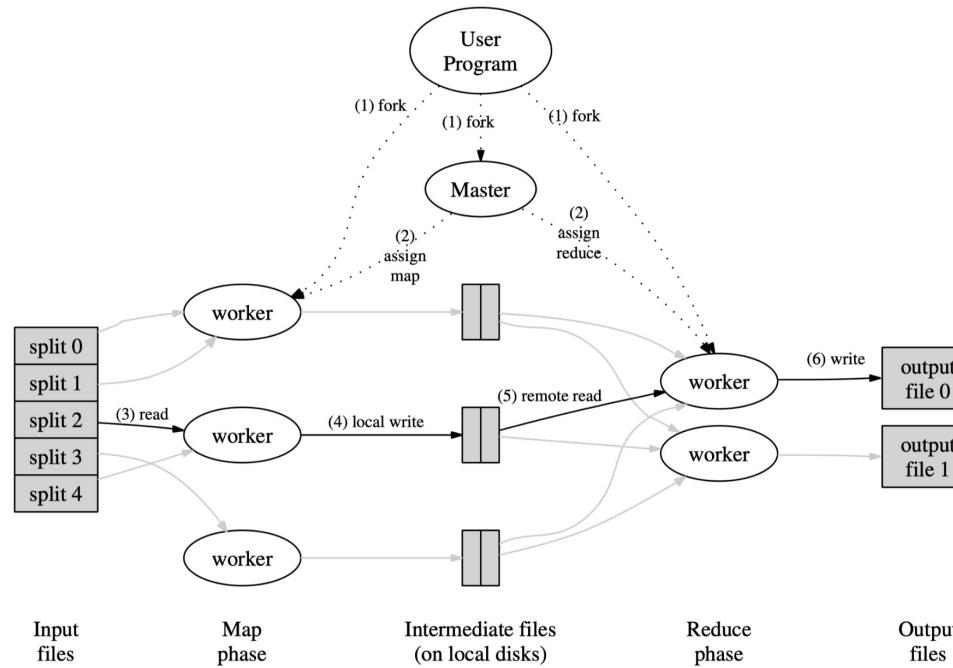
```
apiVersion: mlops.seldon.io/v1alpha1
kind: Pipeline
metadata:
  name: road-counter
spec:
  steps:
    - name: vectorize
    - name: faulty_image_filter
      inputs:
        - vectorize.outputs
    - name: object_detection
      inputs:
        - vectorize.outputs
        - faulty_image_filter.outputs
    . . . .
  output:
    steps:
      - counter
```



Core V1 - Central orchestration



Dataflow architecture

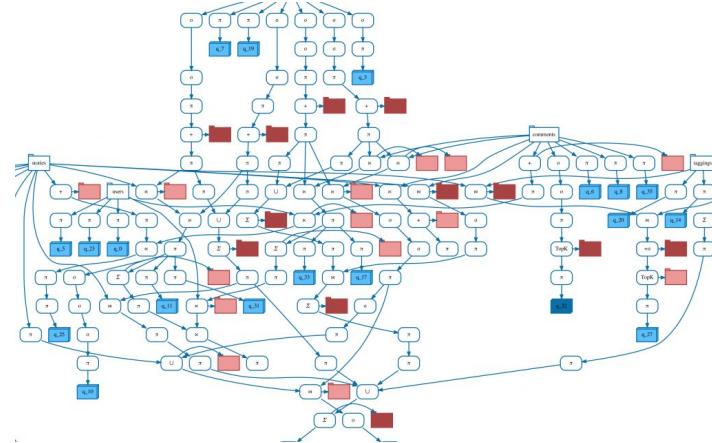


Dean, J. & Ghemawat, S. (2008). MapReduce: simplified data processing on large clusters. Communications of the ACM, 51(1), 107-113.

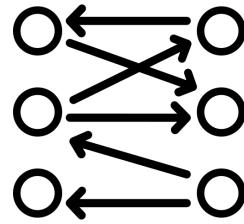
Dataflow vs control flow

“In control flow, the processor follows explicit order, executing instructions one after another. In **dataflow**, by contrast, an instruction is ready to execute as soon as all its inputs are available.”

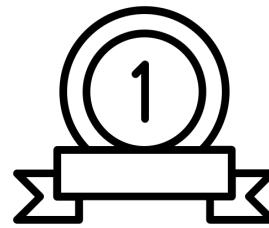
M. Schwarzkopf, *The Remarkable Utility of Dataflow Computing*



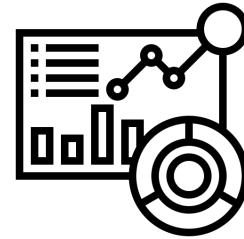
Dataflow features



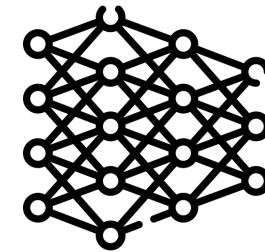
Separation of data
and operations



Data as a first
class citizen

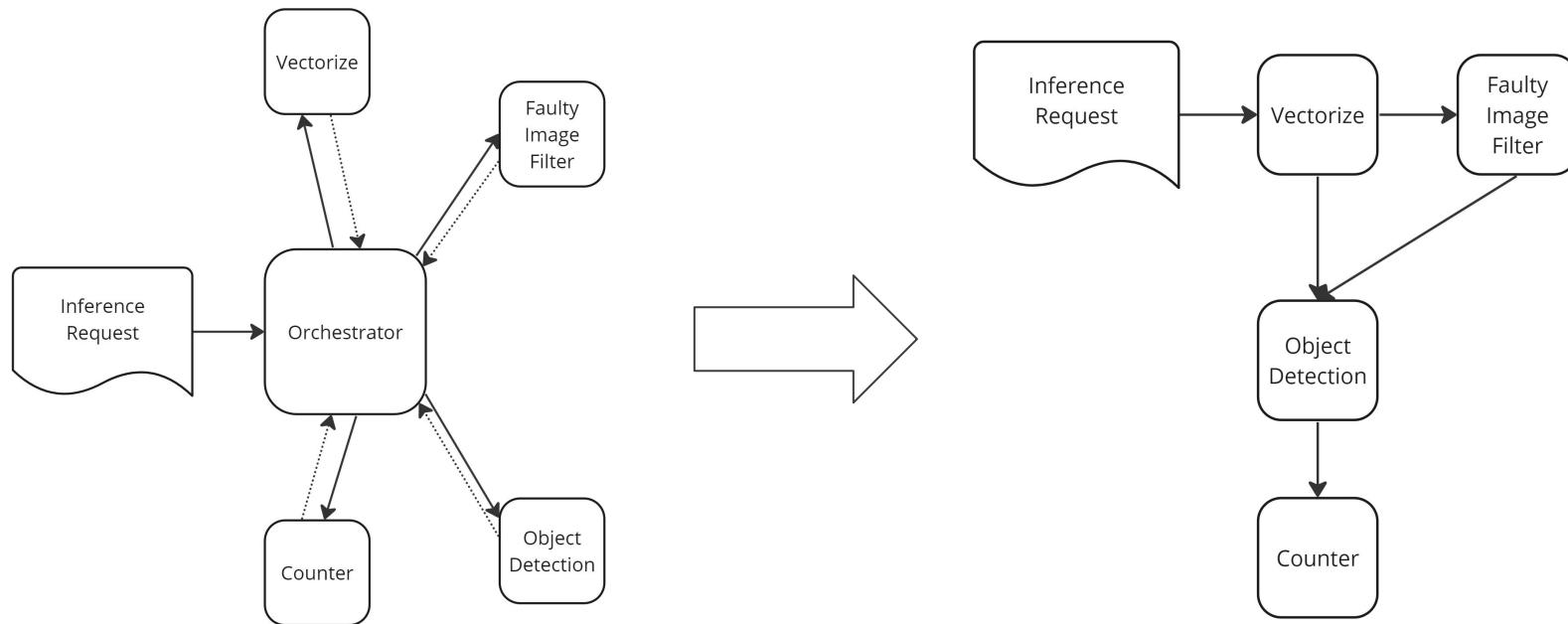


Dataflow graph of
the entire system

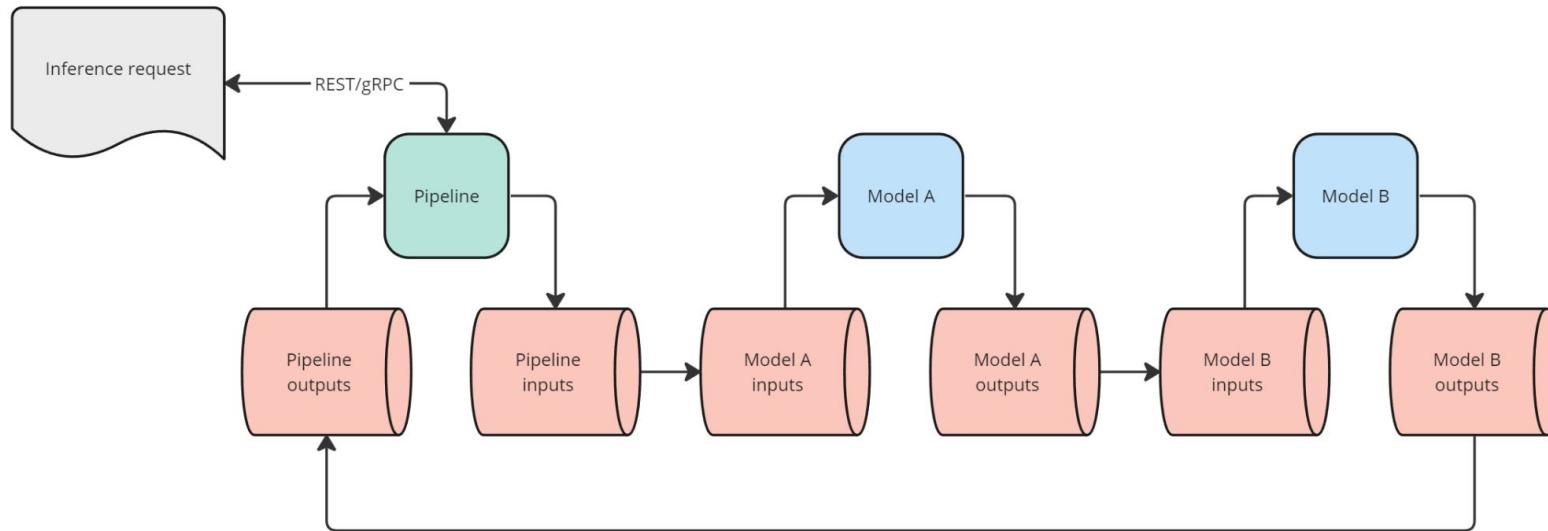


Decentralisation

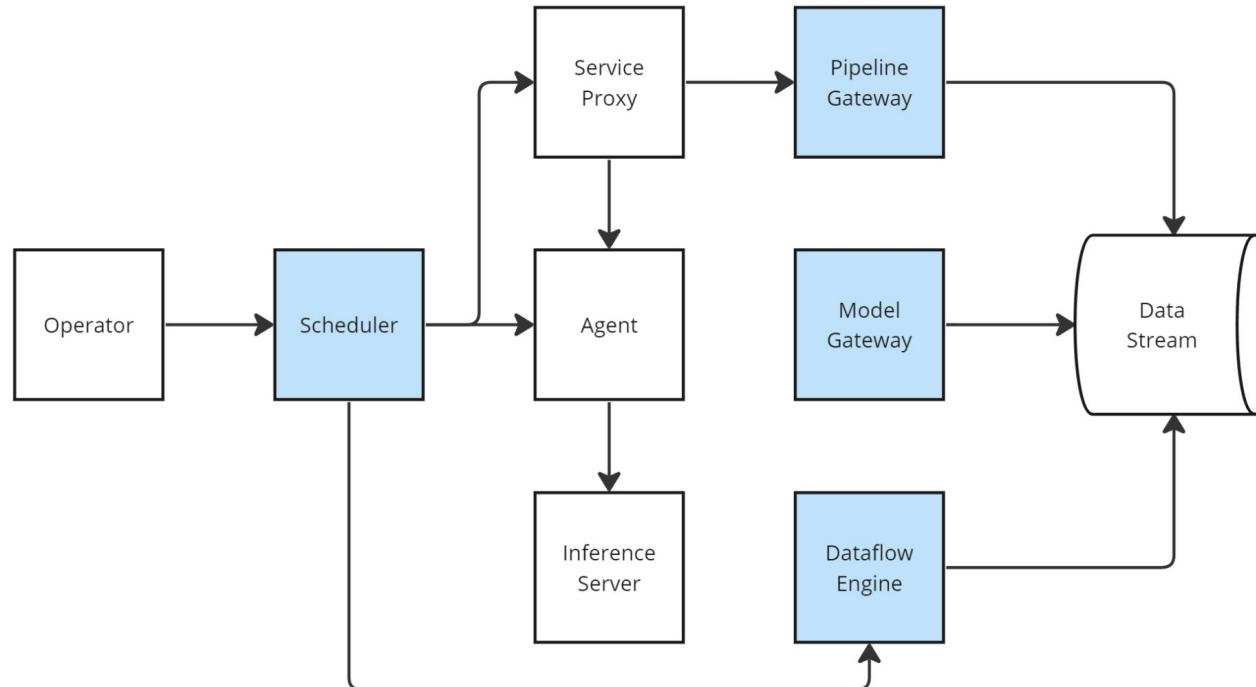
Dataflow and inference graph



Role of streaming in dataflow



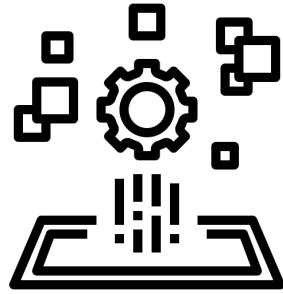
Control plane



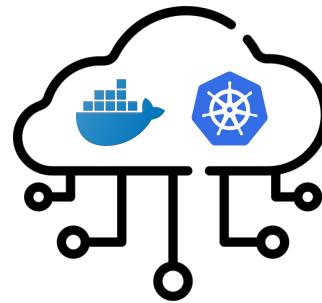


Part II – Implementation

Tech Stack – Constraints



OSS

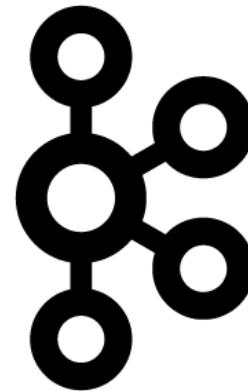


Platform agnostic



Lightweight

Tech Stack – Contenders

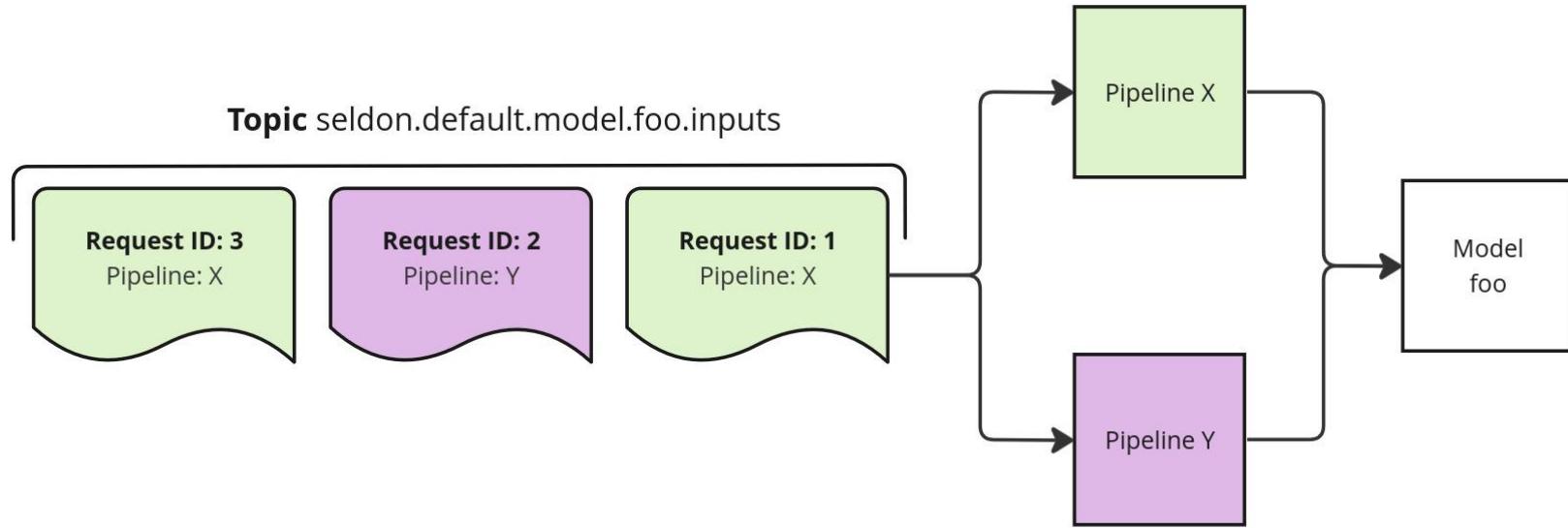


kafka

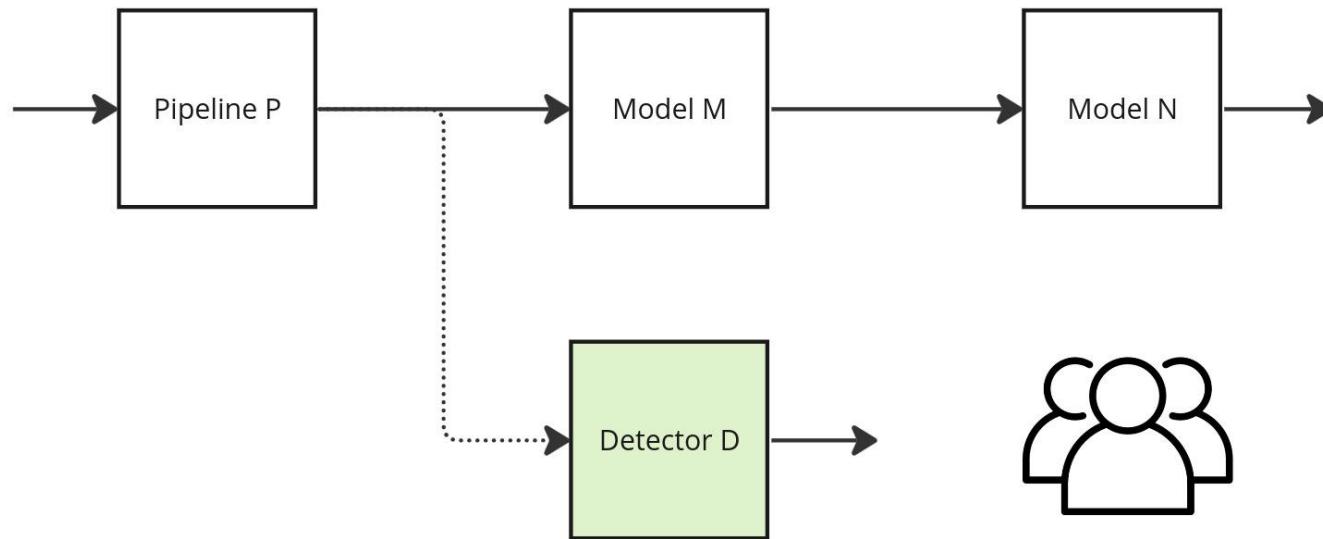
RabbitMQ



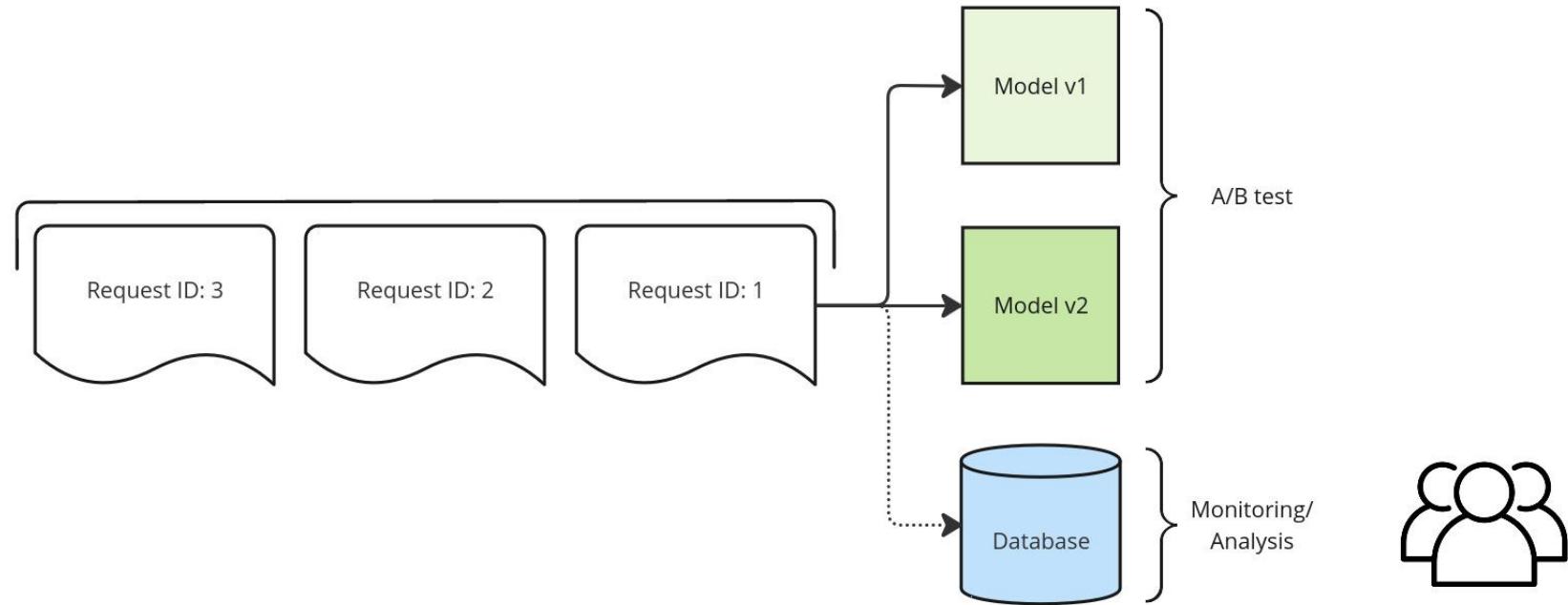
Pub/Sub – Multiplexing Pipelines



Pub/Sub – Extending Pipelines



Pub/Sub – Repeatable Streams



Tech Stack – Choices

```
fun <T> KStream<T, TRecord>.filterForPipeline(pipelineName: String): KStream<T, TRecord> {  
    return this  
        .transformValues(ValueTransformerSupplier { PipelineNameFilter(pipelineName) })  
        .filterNot { _, value -> value == null }  
}
```

```
private fun buildInputInputStream(builder: StreamsBuilder) {  
    val s1 = builder  
        .stream(inputTopic.topicName, consumerSerde)  
        .filterForPipeline(inputTopic.pipelineName)  
        .unmarshallInferenceV2Request()  
        .filterRequests(inputTopic.pipelineName, inputTopic.topicName, tensors, tensorRenaming)  
        // handle cases where there are no tensors we want  
        .filter { _, value -> value.inputsList.size != 0 }  
        .batchMessages(batchProperties)  
        .marshallInferenceV2Request()
```

Anatomy of a Topic Name

<prefix>.<namespace>.<pipeline|model>.<name>.<inputs|outputs>

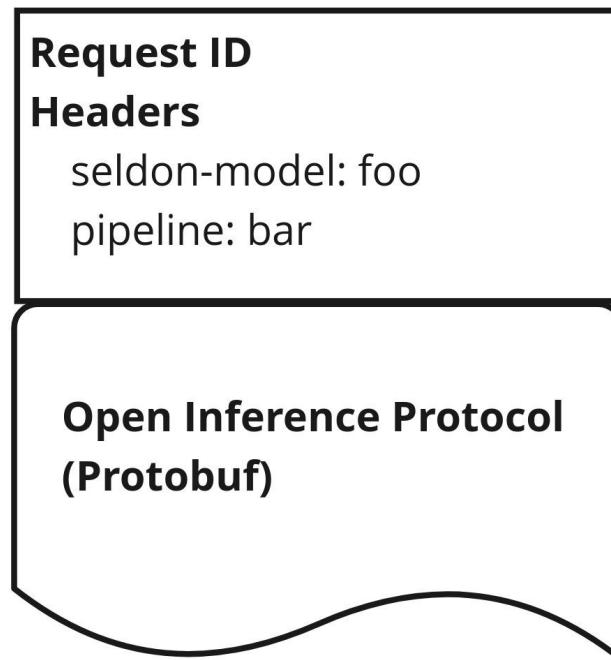
seldon.default.pipeline.foo.inputs

seldon.recommendations.model.bar.outputs

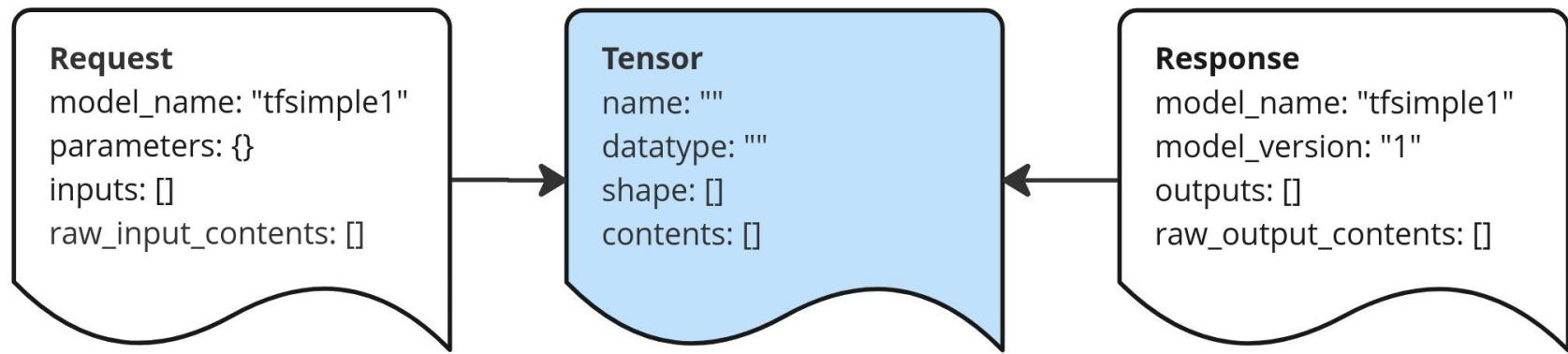
<prefix>.<namespace>.errors.errors

ml.default.errors.errors

Anatomy of an Inference Message



Open Inference Protocol



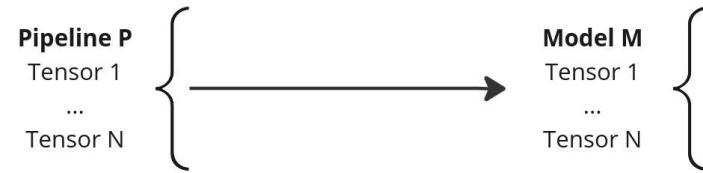
Open Inference Protocol – Batching

Tensor

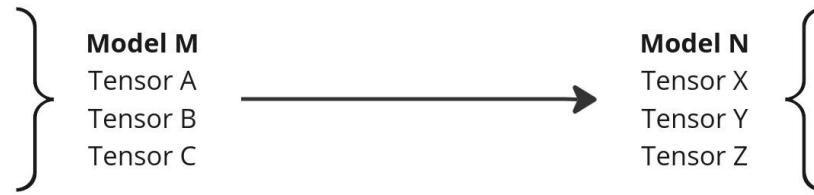
shape: [BATCH_SIZE, ...]

...

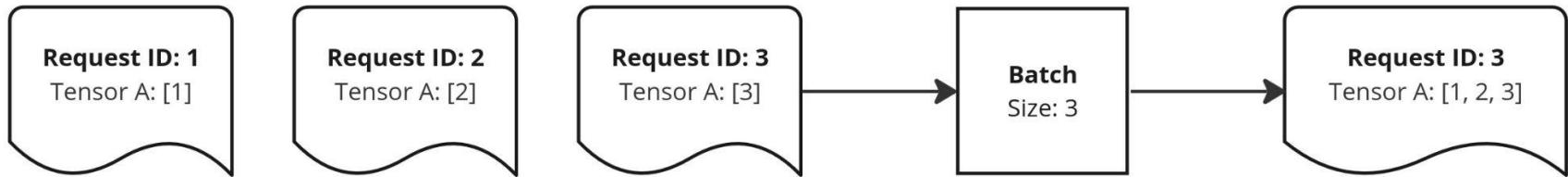
Dataflow Operations – Topic Chaining



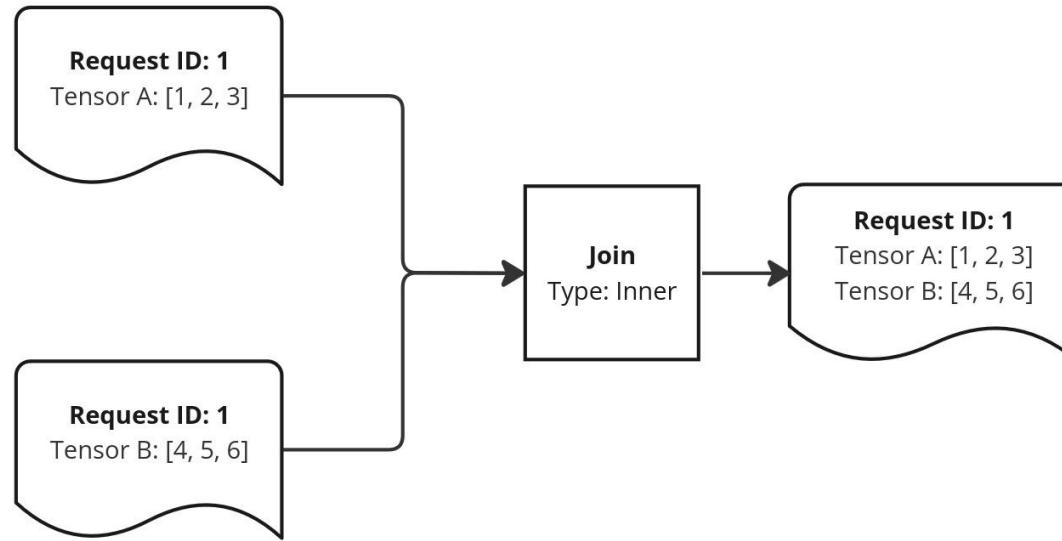
Dataflow Operations – Tensor Projection



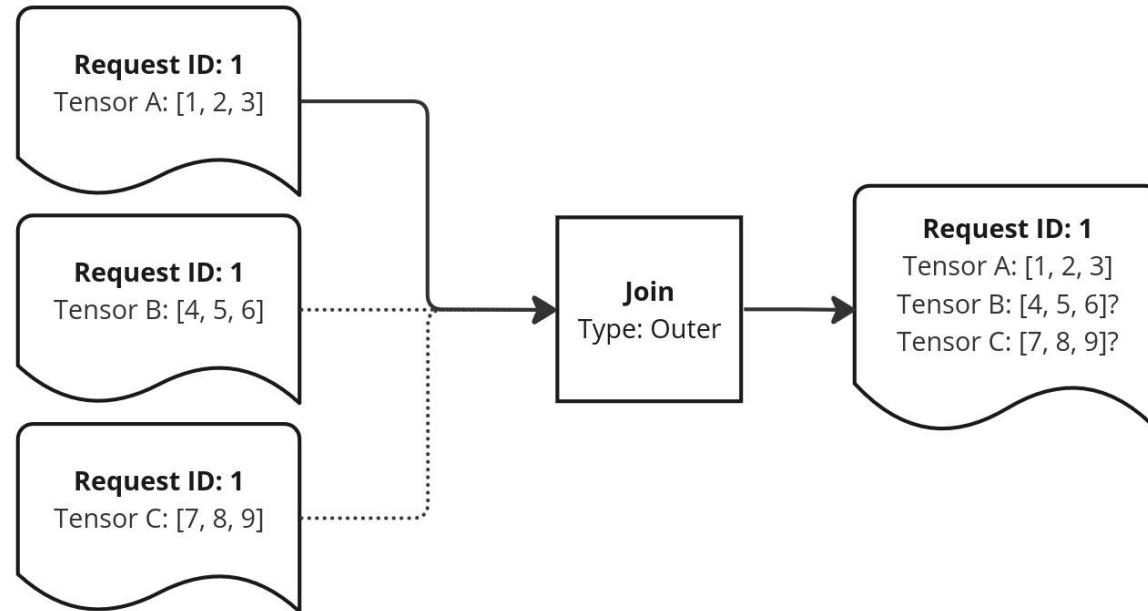
Dataflow Operations – Batching



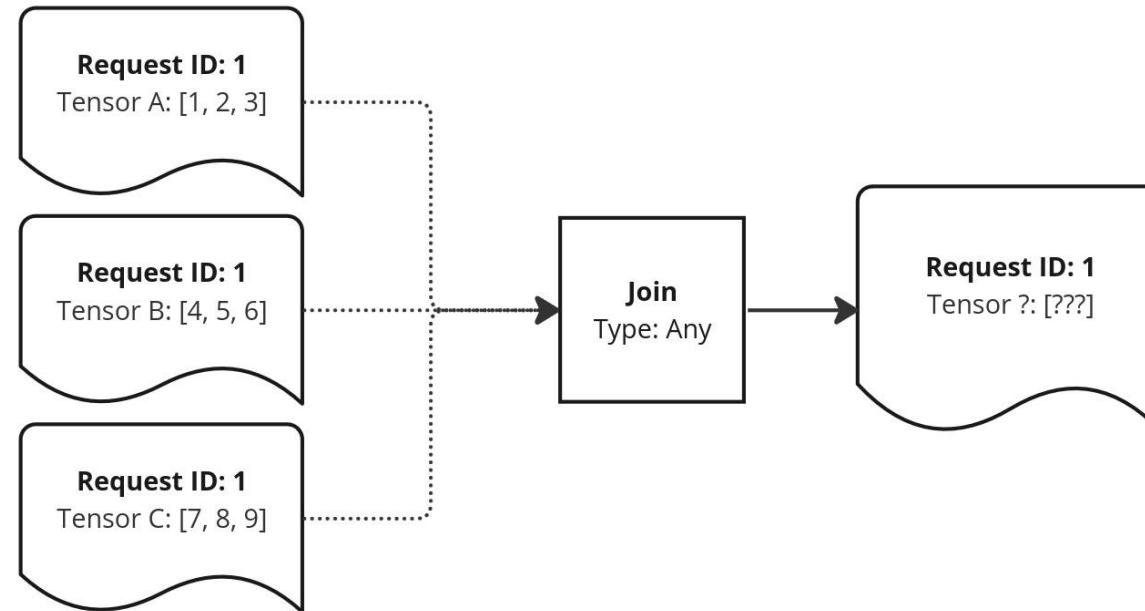
Dataflow Operations – Inner Join



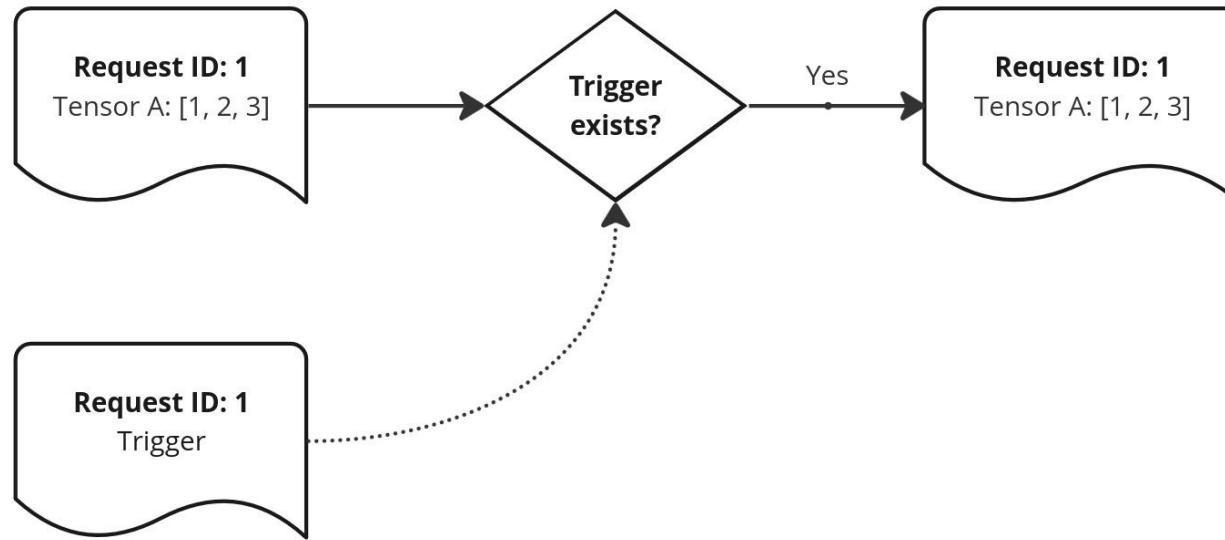
Dataflow Operations – Outer Join



Dataflow Operations – Any Join



Dataflow Operations – Triggers



Topologies

Core v2 Pipeline

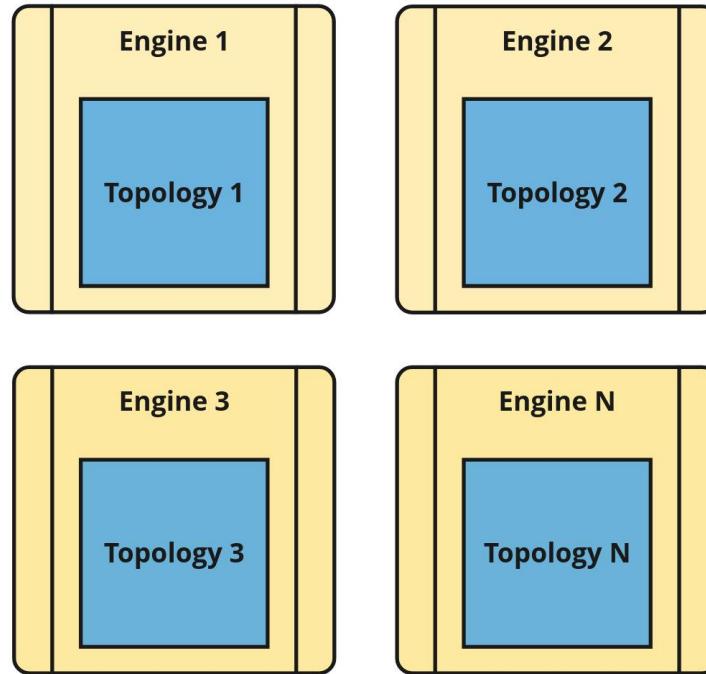
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KStream Topology

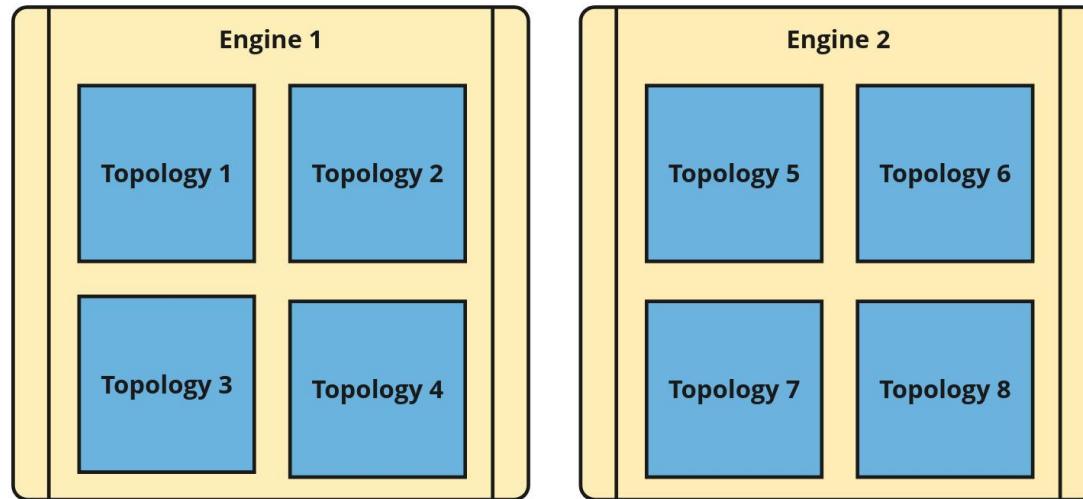
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    - name: faulty_image_filter
      inputs:
        - vectorize.outputs
    - name: object_detection
      inputs:
        - vectorize.outputs
        - faulty_image_filter.outputs
...
...
```

```
val builder = StreamsBuilder()
builder
  .stream(inputTopic.topicName, consumerSerde)
  .filterForPipeline(inputTopic.pipelineName)
...
val topology = builder.build()
```

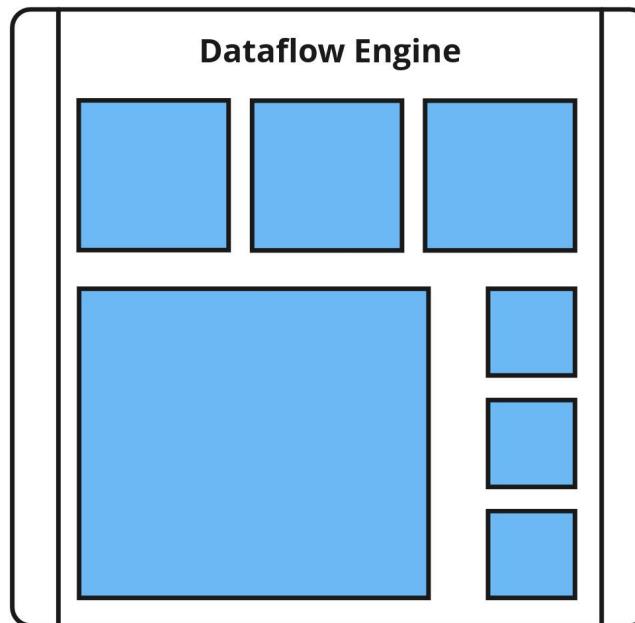
Pipeline Allocation – 1 Topology = 1 Engine



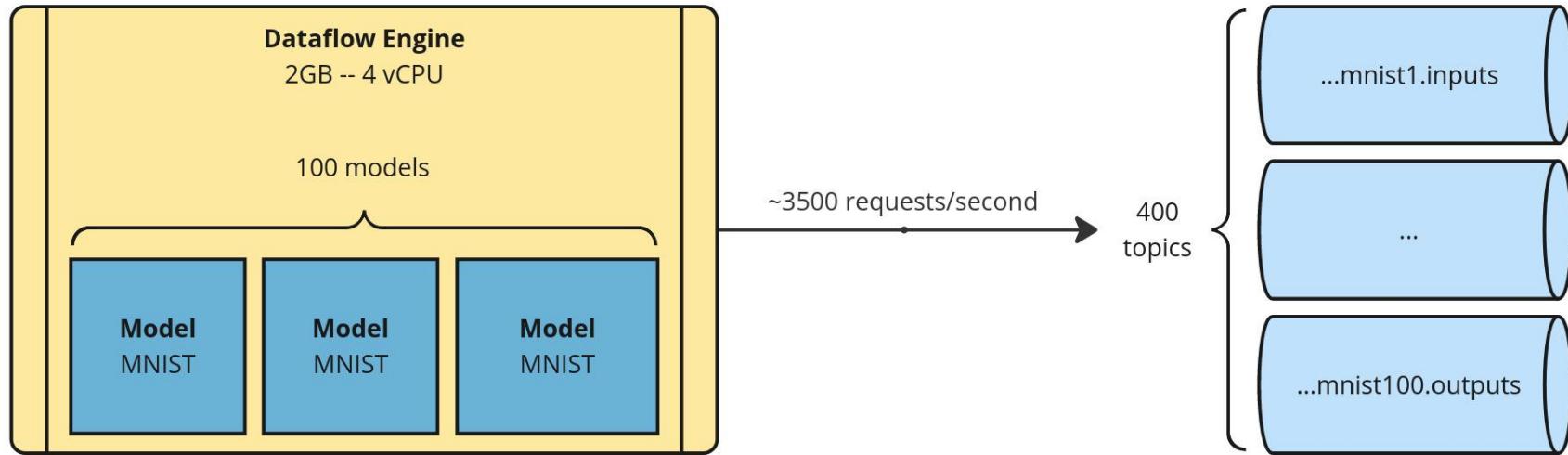
Pipeline Allocation – Shared Engines



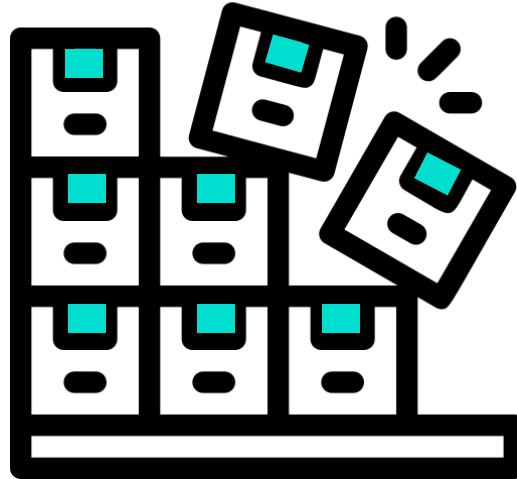
Pipeline Allocation – Threads



How Many Is Too Many?



How Many Is Too Many?

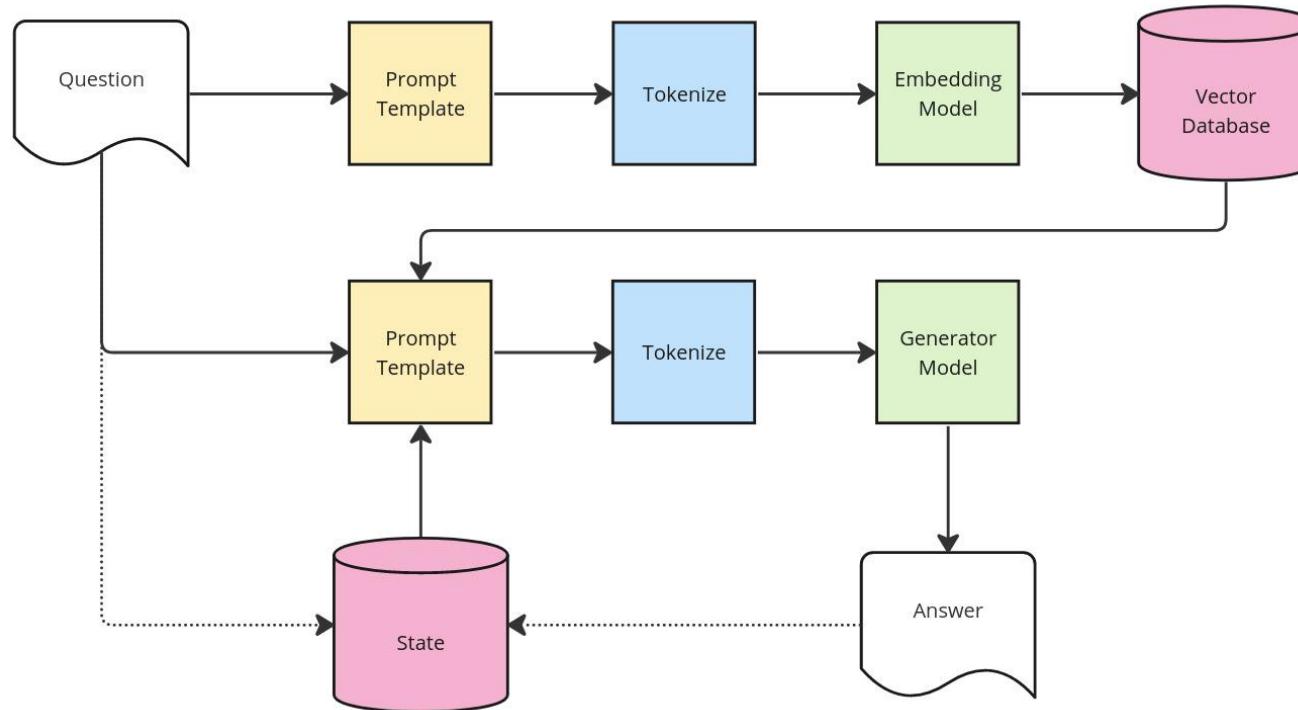


[KSQL Limitations in Confluent Cloud](#)

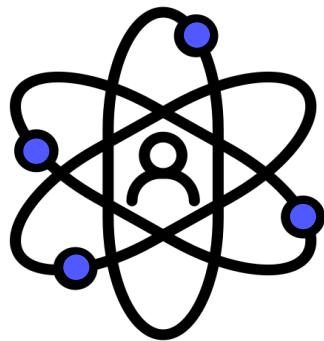
[Kafka Summit 2022 - Modular Topologies](#)

[KIP-809 \(Modular Topologies\)](#)

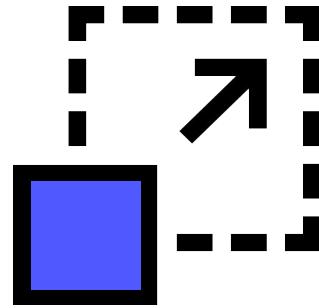
Advanced ML Applications



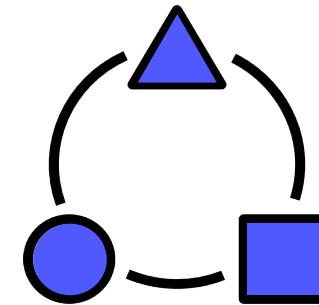
Challenges



Dynamism

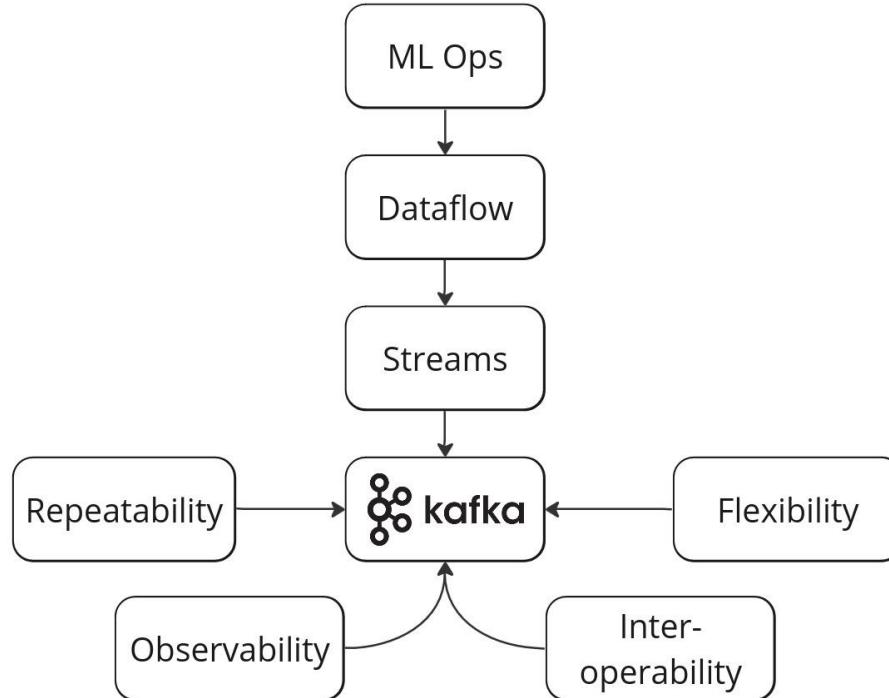


Scalability



Variety

Thanks for listening!



The Seldon Core v2 Team

Core v2 on GitHub



SCAN ME

Team



Clive Cox
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MLOps Engineer



Adrian Gonzalez-Martin
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