Real-Time Predictive Modeling with MLServer, MLFlow, and Apache Beam

BEAM SUMMIT NYC 2025

Devon Peticolas & Jeswanth Yadagani

Oden Technologies

Agenda

- Background
  - Who are we?
  - The problem that we're solving
  - A quick architecture overview
- Training
  - Getting the data (Clickhouse)
  - Training our models (SKLearn)
  - Managing our models (MLFlow)
- Deploying
  - Syncing MFlow, MLServer, and Dataflow via GCS
- Scoring
  - Getting the data (PubSub)
  - Tensor Forming (Beam)
  - Scoring (MLServer)
  - Embedded vs External Inference
- After v1
  - Cost Optimization
  - Shared Resources
- Conclusions
- Q&A

Background

How we got here

Devon Peticolas

Principal Engineer at Oden

One of Oden's first engineers
(responsible for many bad engineering decisions but **Beam is not one of them**)

I wrote my first beam job in 2018

This is my **fourth** Beam Summit!

Jeswanth Yadagani

Senior ML Engineer at Oden

Not one of Oden's first engineers
(still feeling the pain for those other bad engineering decisions)

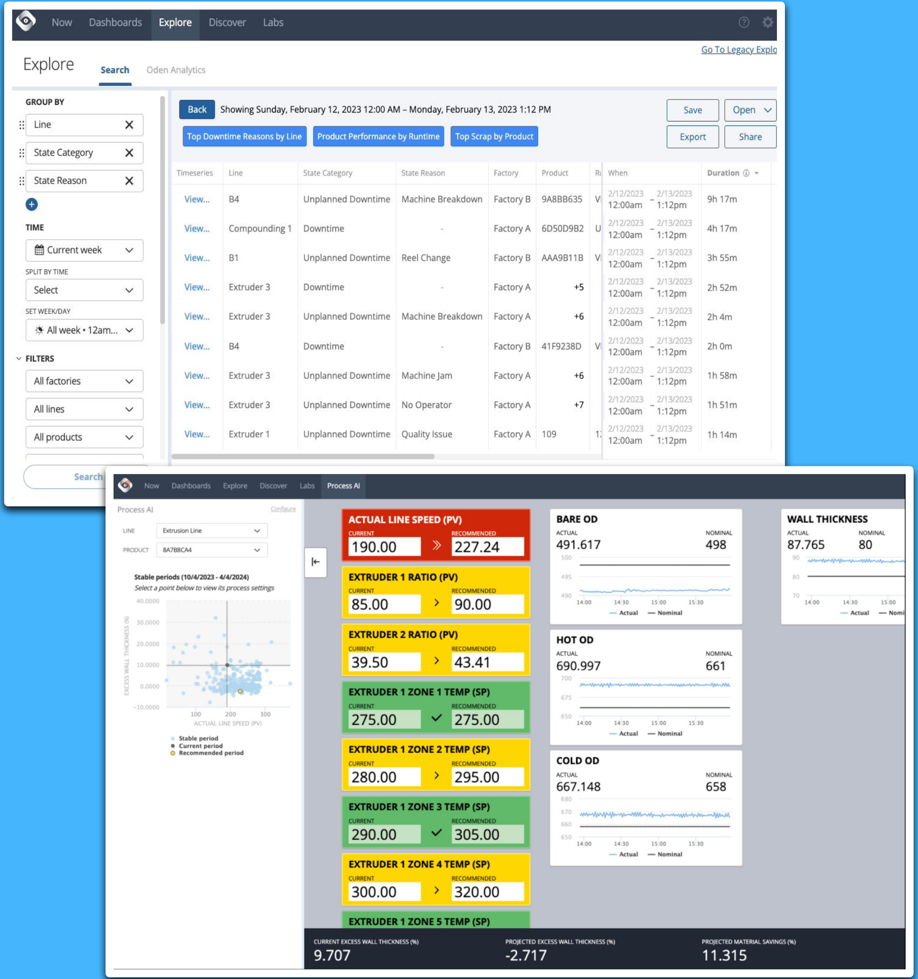
I wrote my first beam job in 2020

This is my **third** Beam Summit!

Who is Oden Technologies?

Oden Technologies

- Think “New Relic but for manufacturing”
- Real-time and historical analytics for manufacturing
- Customers in plastics, chemical, paper
- We have lots of time-series data
- Productized machine learning an AI



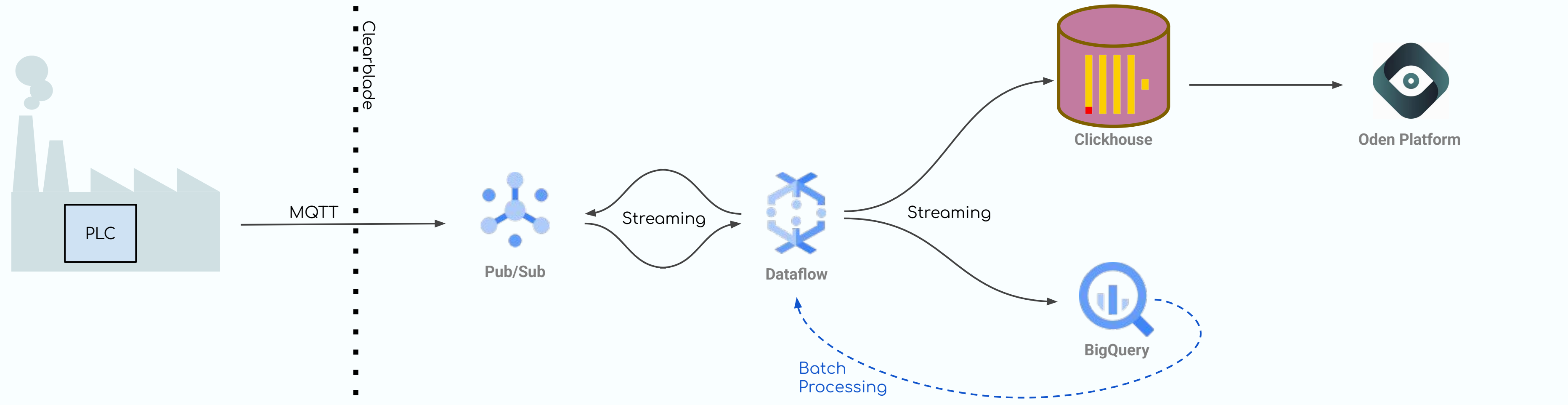
How Does Oden Use Beam

Streaming

- Processing of “raw” manufacturing data via MQTT (Clearblade to PubSub)
- Stateful and windowed transformation and state change detection
- Delivery into Clickhouse and BigQuery

Batch

- The same jobs we run in streaming but in a special “batch mode” for:
  - Backfills
  - Late Data Processing
  - Outage Recovery



Example Job: Calculated Metrics

User Has

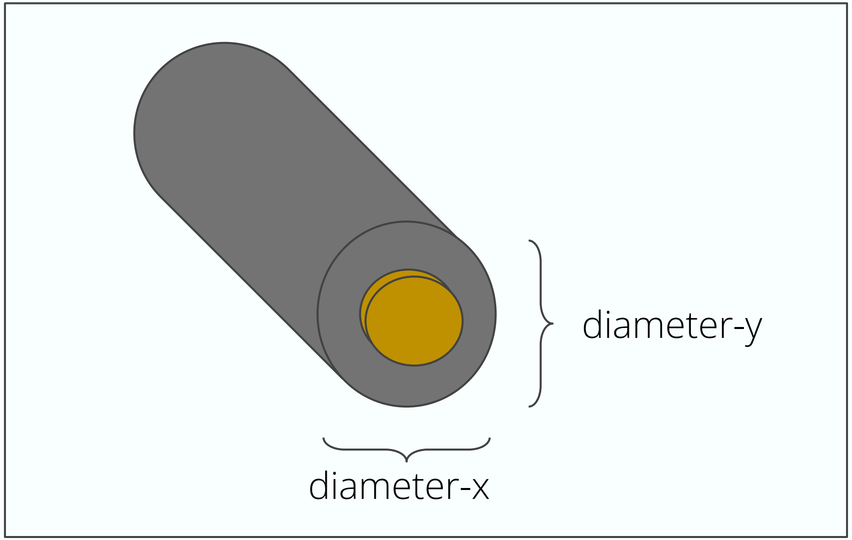
`diameter-x` and `diameter-y`

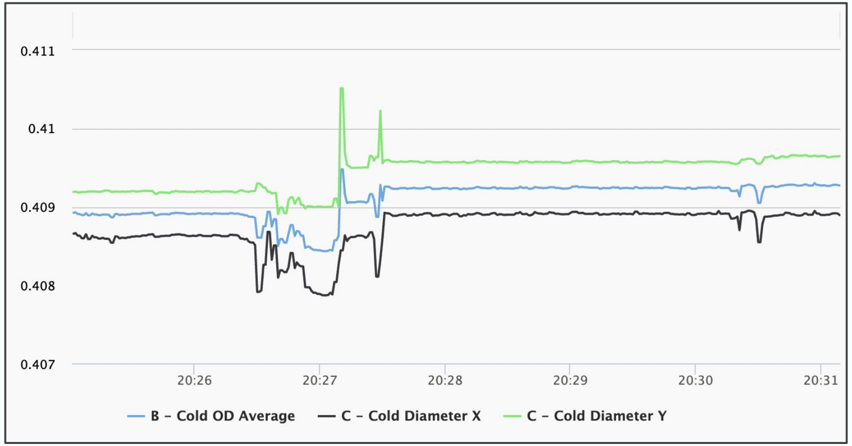
User Wants

```
avg-diameter = (diameter-x + diameter-y) / 2
```

Calculated Metrics

- New “calculated” metrics need to be computed in real-time
- Components come from different sensors
- User-defined formulas stored in Postgres
- New calculated metrics are treated just like “real” metrics





Predictive Metrics

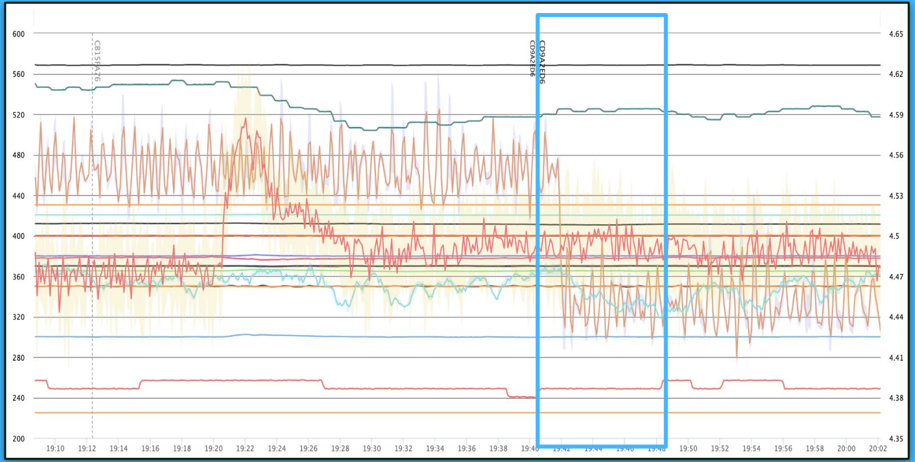
Customers perform "off line" tests of their product to determine quality

- Paper
  - Stretch until tear testing
  - Folding and crushing
- Ink
  - Color spectrum testing
  - Particulate distribution testing
- Wire
  - Tensile strength
  - Wall thickness

These measures come 40m to 2d after production.

Hypothesis

In-line measurement can predict off-line quality



Architecture Overview

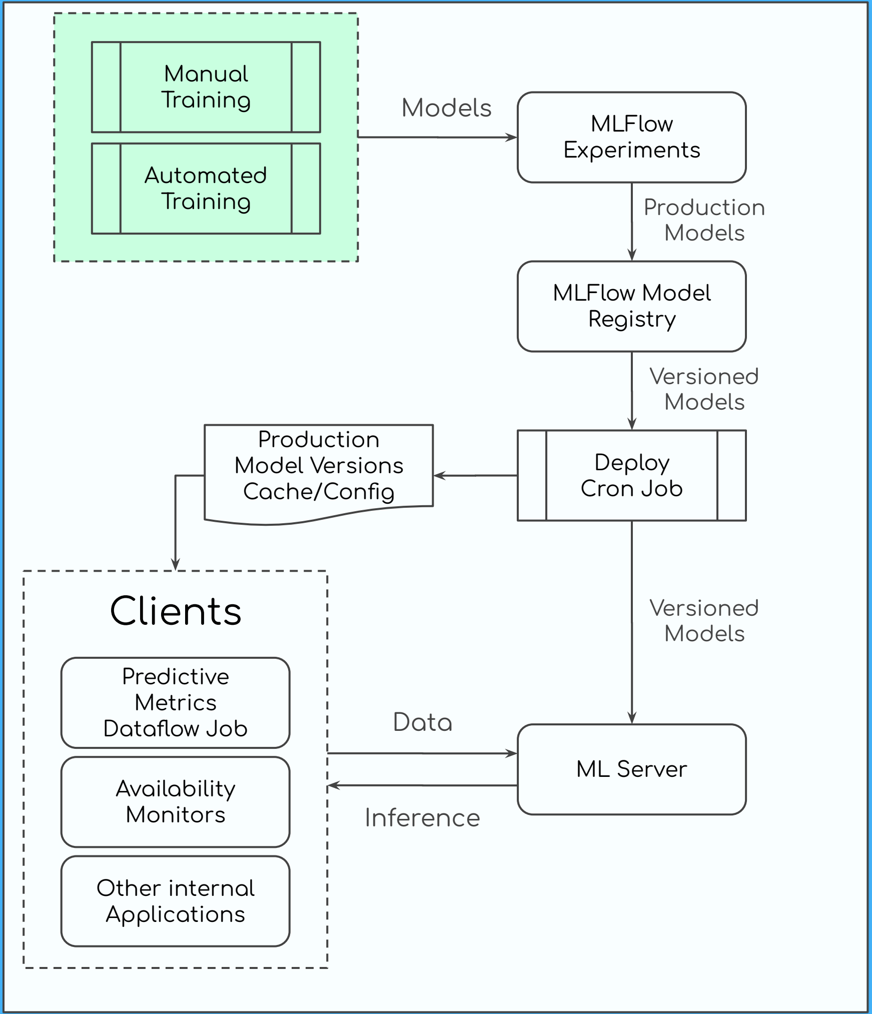
Architecture Overview

- Experiments are conducted locally to fit the appropriate model, features and pipeline.
- Automated Training is orchestrated via Airflow using Cloud Run Jobs.

Apache Airflow

scikit learn

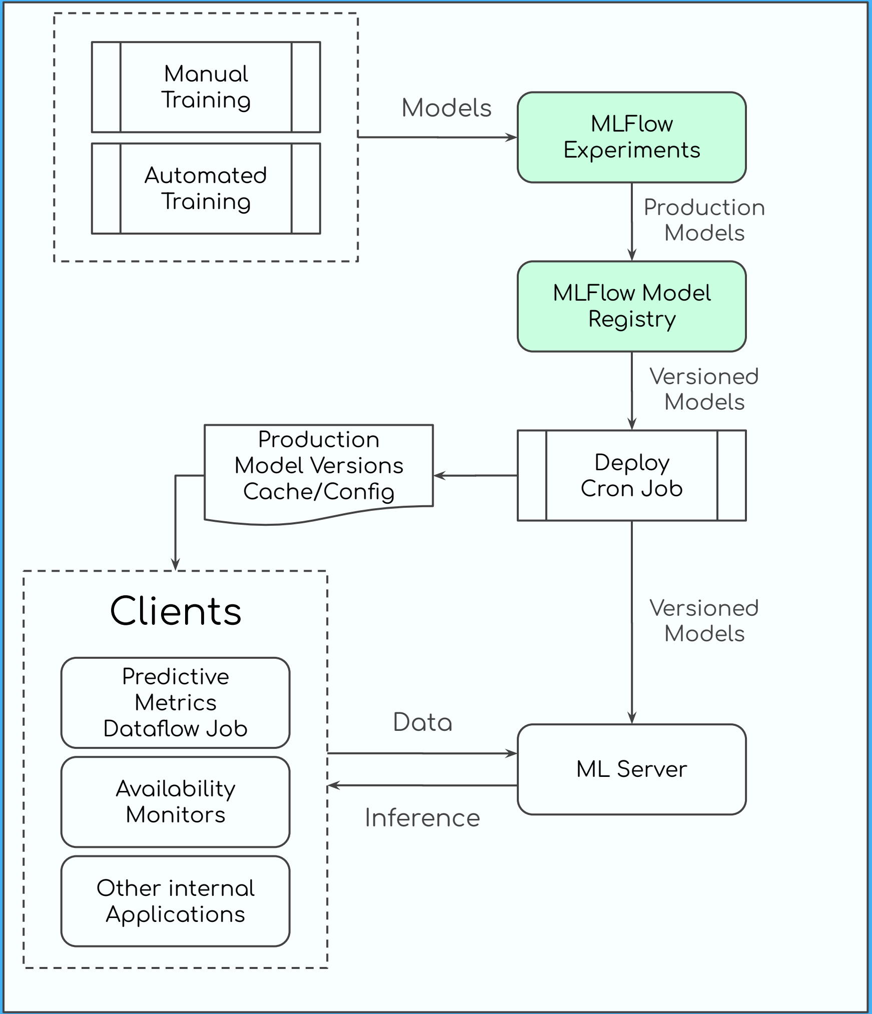
Cloud Run



Architecture Overview

- MLFlow Experiments: Stores information about ML model training and experiments along with metrics, model objects, and supporting artifacts.
- MLFlow Model Registry: Allows versioning of production models.

Cloud Storage
Cloud Run
Cloud SQL



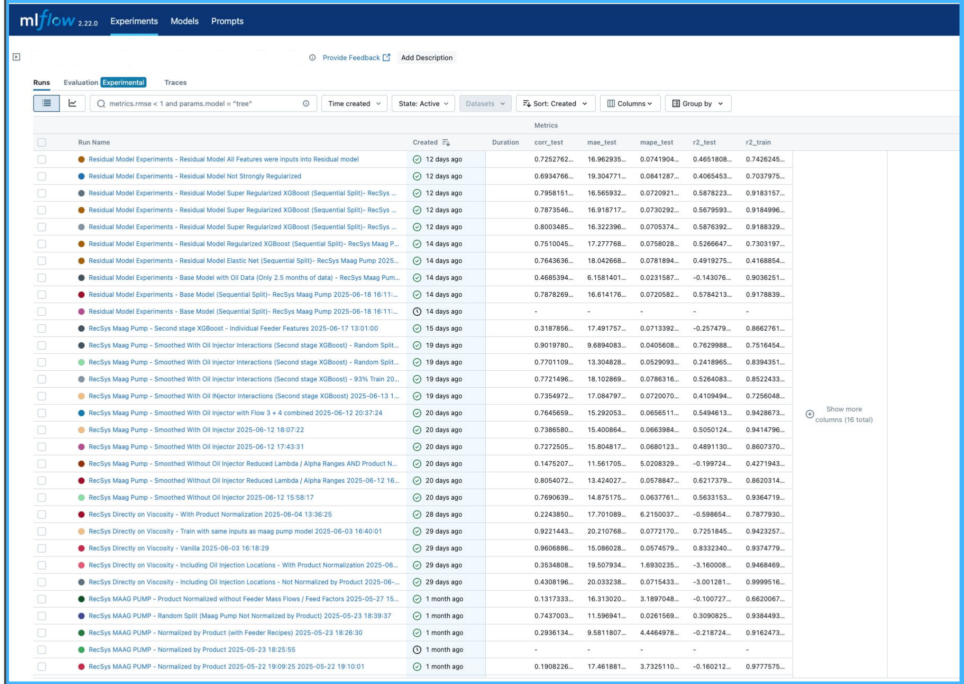
Architecture Overview

- MLFlow Experiments: Stores information about ML model training and experiments along with metrics, model objects, and supporting artifacts.
- MLFlow Model Registry: Allows versioning of production models.

Cloud Storage

Cloud Run

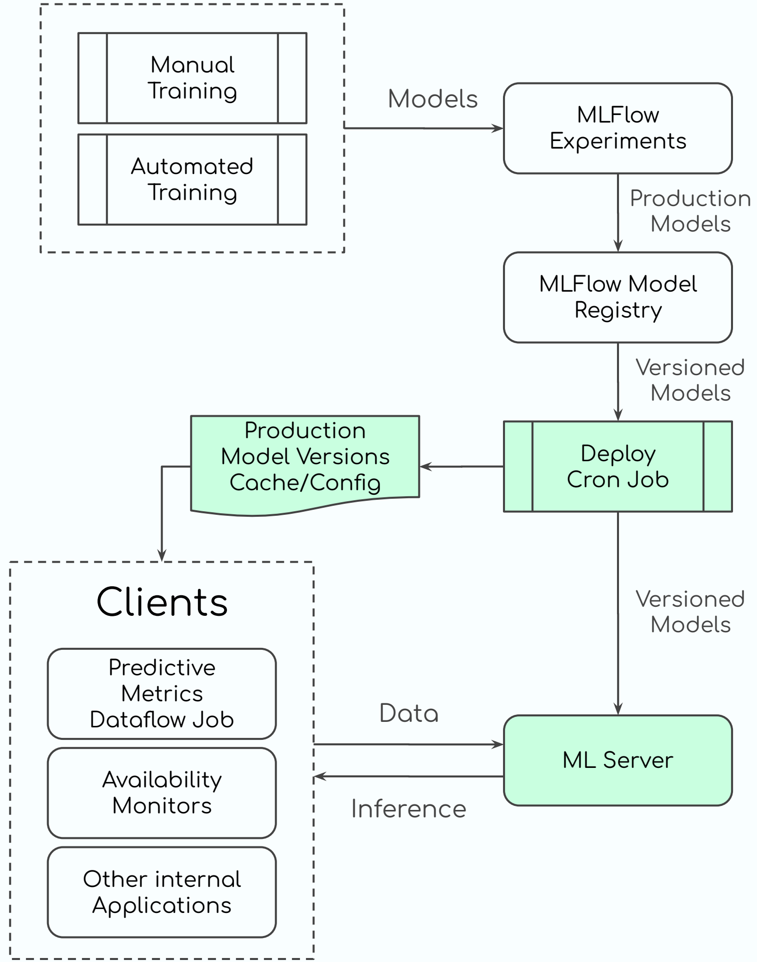
Cloud SQL



Run Name	Created	Duration	corr_test	mae_test	mape_test	r2_test	r2_train
Residual Model Experiments - Residual Model All Features were inputs into Residual model	12 days ago		0.7252762...	16.962935...	0.0741904...	0.4651808...	0.7426245...
Residual Model Experiments - Residual Model Not Strongly Regularized	12 days ago		0.6934766...	19.304771...	0.0841287...	0.4065453...	0.7037975...
Residual Model Experiments - Residual Model Super Regularized XGBoost (Sequential Split)- RecSys ...	12 days ago		0.7958151...	16.565932...	0.0720921...	0.5878223...	0.9183157...
Residual Model Experiments - Residual Model Super Regularized XGBoost (Sequential Split)- RecSys ...	12 days ago		0.7873546...	16.918717...	0.0730292...	0.5679593...	0.9184996...
Residual Model Experiments - Residual Model Super Regularized XGBoost (Sequential Split)- RecSys ...	12 days ago		0.8003485...	16.322396...	0.0705374...	0.5876392...	0.9188329...
Residual Model Experiments - Residual Model Regularized XGBoost (Sequential Split)- RecSys Maag P...	14 days ago		0.7510045...	17.277768...	0.0758028...	0.5266647...	0.7303197...
Residual Model Experiments - Residual Model Elastic Net (Sequential Split)- RecSys Maag Pump 2025...	14 days ago		0.7643636...	18.042668...	0.0781894...	0.4919275...	0.4168854...
Residual Model Experiments - Base Model with Oil Data (Only 2.5 months of data) - RecSys Maag Pum...	14 days ago		0.4685394...	6.1581401...	0.0231587...	-0.143076...	0.9036251...
Residual Model Experiments - Base Model (Sequential Split)- RecSys Maag Pump 2025-06-18 16:11:...	14 days ago		0.7878269...	16.614176...	0.0720582...	0.5784213...	0.9178839...
Residual Model Experiments - Base Model (Sequential Split)- RecSys Maag Pump 2025-06-18 16:11:...	14 days ago		-	-	-	-	-
RecSys Maag Pump - Second stage XGBoost - Individual Feeder Features 2025-06-17 13:01:00	15 days ago		0.3187856...	17.491757...	0.0713392...	-0.257479...	0.8662761...
RecSys Maag Pump - Smoothed With Oil Injector Interactions (Second stage XGBoost) - Random Split...	19 days ago		0.9019780...	9.6894083...	0.0405608...	0.7629988...	0.7516454...
RecSys Maag Pump - Smoothed With Oil Injector Interactions (Second stage XGBoost) - Random Split...	19 days ago		0.7701109...	13.304828...	0.0529093...	0.2418965...	0.8394351...
RecSys Maag Pump - Smoothed With Oil Injector Interactions (Second stage XGBoost) - 93% Train 20...	19 days ago		0.7721496...	18.102869...	0.0786316...	0.5264083...	0.8522433...
RecSys Maag Pump - Smoothed With Oil INjector Interactions (Second stage XGBoost) 2025-06-13 1...	19 days ago		0.7354972...	17.084797...	0.0720070...	0.4109494...	0.7256048...
RecSys Maag Pump - Smoothed With Oil Injector with Flow 3 + 4 combined 2025-06-12 20:37:24	20 days ago		0.7645659...	15.292053...	0.0656511...	0.5494613...	0.9428673...
RecSys Maag Pump - Smoothed With Oil Injector 2025-06-12 18:07:22	20 days ago		0.7386580...	15.400864...	0.0663984...	0.5050124...	0.9414796...
RecSys Maag Pump - Smoothed With Oil Injector 2025-06-12 17:43:31	20 days ago		0.7272505...	15.804817...	0.0680123...	0.4891130...	0.8607370...
RecSys Maag Pump - Smoothed Without Oil Injector Reduced Lambda / Alpha Ranges AND Product N...	20 days ago		0.1475207...	11.561705...	5.0208329...	-0.199724...	0.4271943...
RecSys Maag Pump - Smoothed Without Oil Injector Reduced Lambda / Alpha Ranges 2025-06-12 16...	20 days ago		0.8054072...	13.424027...	0.0578847...	0.6217379...	0.8620314...
RecSys Maag Pump - Smoothed Without Oil Injector 2025-06-12 15:58:17	20 days ago		0.7690639...	14.875175...	0.0637761...	0.5633153...	0.9364719...
RecSys Directly on Viscosity - With Product Normalization 2025-06-04 13:36:25	28 days ago		0.2243850...	17.701089...	6.2150037...	-0.598654...	0.7877930...
RecSys Directly on Viscosity - Train with same inputs as maag pump model 2025-06-03 16:40:01	29 days ago		0.9221443...	20.210768...	0.0772170...	0.7251845...	0.9423257...
RecSys Directly on Viscosity - Vanilla 2025-06-03 16:18:29	29 days ago		0.9606886...	15.086028...	0.0574579...	0.8332340...	0.9374779...
RecSys Directly on Viscosity - Including Oil Injection Locations - With Product Normalization 2025-06...	29 days ago		0.3534808...	19.507934...	1.6930235...	-3.160008...	0.9468469...
RecSys Directly on Viscosity - Including Oil Injection Locations - Not Normalized by Product 2025-06-...	29 days ago		0.4308196...	20.033238...	0.0715433...	-3.001281...	0.9999516...
RecSys MAAG PUMP - Product Normalized without Feeder Mass Flows / Feed Factors 2025-05-27 15...	1 month ago		0.1317333...	16.313020...	3.1897048...	-0.100727...	0.6620067...
RecSys MAAG PUMP - Random Split (Maag Pump Not Normalized by Product) 2025-05-23 18:39:37	1 month ago		0.7437003...	11.596941...	0.0261569...	0.3090825...	0.9384493...
RecSys MAAG PUMP - Normalized by Product (with Feeder Recipes) 2025-05-23 18:26:30	1 month ago		0.2936134...	9.5811807...	4.4464978...	-0.218724...	0.9162473...
RecSys MAAG PUMP - Normalized by Product 2025-05-23 18:25:55	1 month ago		-	-	-	-	-
RecSys MAAG PUMP - Normalized by Product 2025-05-22 19:09:25 2025-05-22 19:10:01	1 month ago		0.1908226...	17.461881...	3.7325110...	-0.160212...	0.9777575...

Architecture Overview

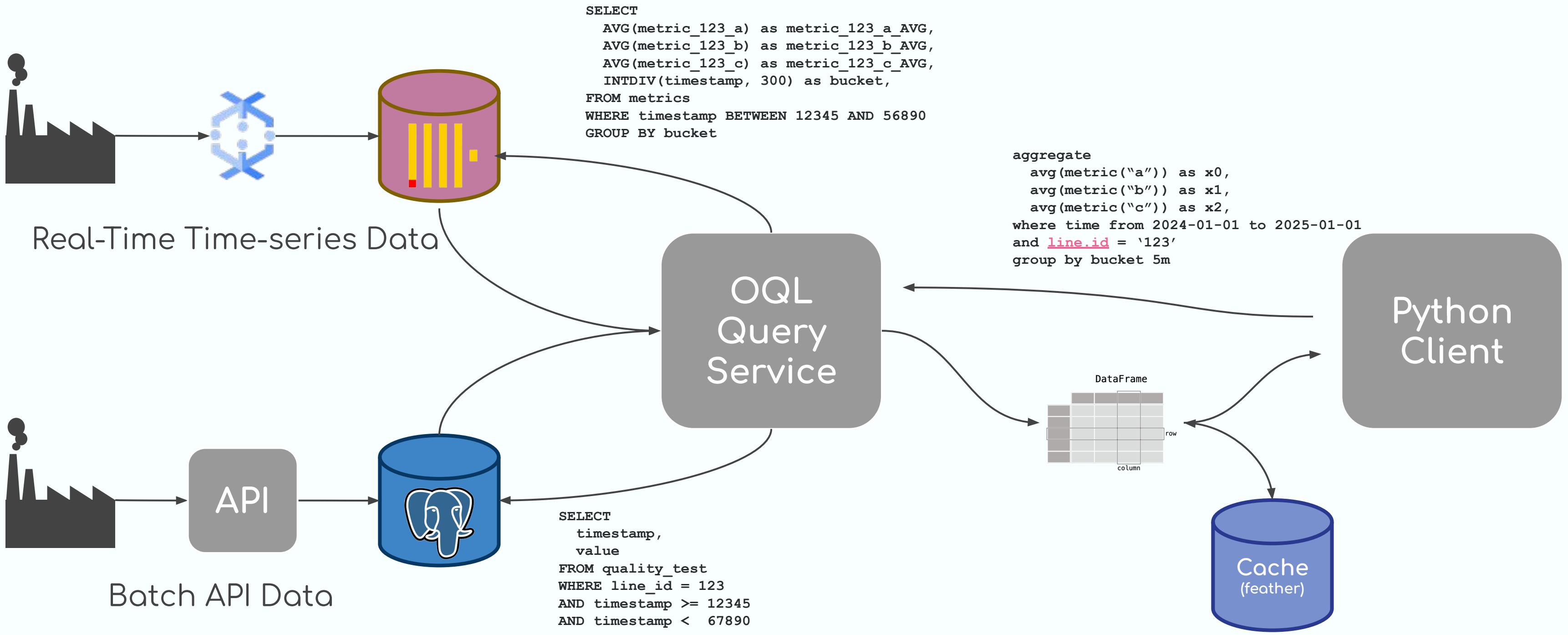
- Deploy Cron Job is scheduled using Airflow
- Models from MLFlow Model Registry are deployed onto MLServer
- Production Model Version information is stored in GCS



Training our Models

With SKLearn and MLFlow

Getting Data for Training

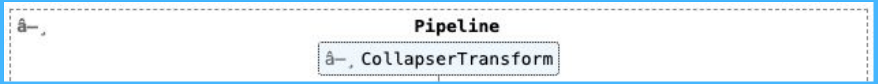


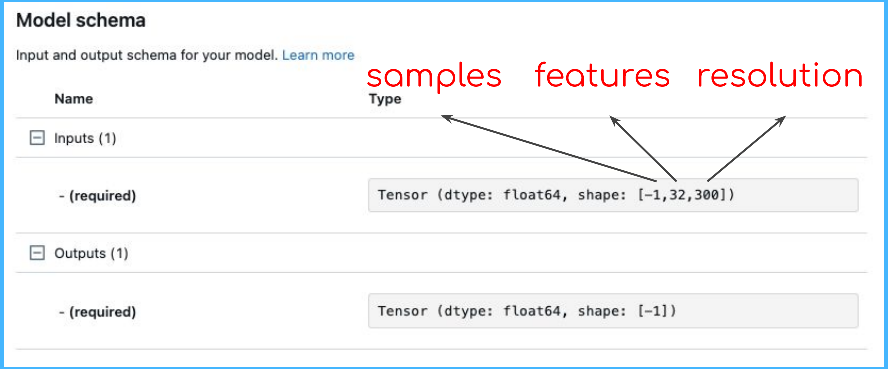
Training the Model

- Data Scientists conduct EDA, feature engineering and builds an sklearn pipeline.

Training the Model

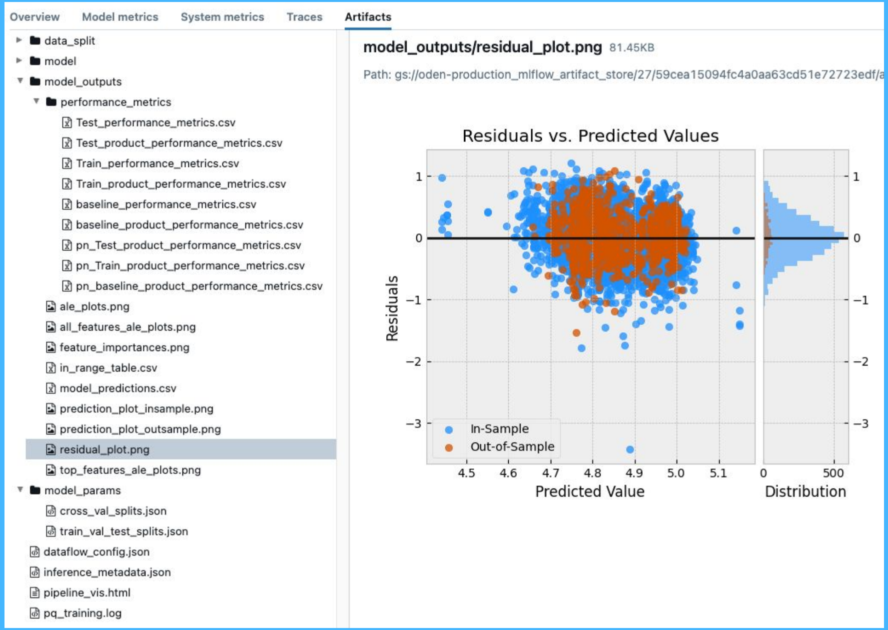
- Data Scientists conduct EDA, feature engineering and builds an sklearn pipeline.
- **The first layer of the pipeline is designed to support time shifted features from the low resolution data.**





Training the Model

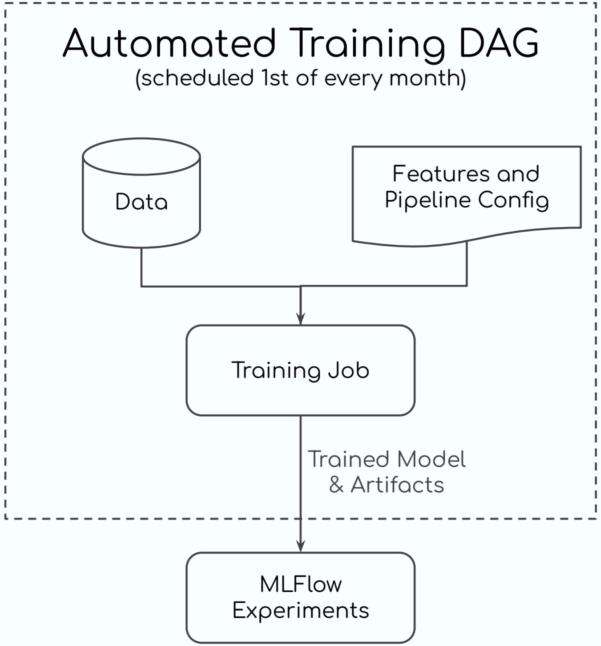
- Data Scientists conduct EDA, feature engineering and builds an sklearn pipeline.
- The first layer of the pipeline is designed to support time shifted features from the low resolution data.
- **All the model experiments are logged to MLFlow along with test statistics and supporting artifacts for peer review.**



Metric	Value
train_corr	0.9185993286254339
test_corr	0.949061721727258
train_r2	0.8408351971582717
test_r2	0.8948399662709521

Training the Model

- Data Scientists conduct EDA, feature engineering and builds an sklearn pipeline.
- The first layer of the pipeline is designed to support time shifted features from the low resolution data.
- All the model experiments are logged to MLFlow along with test statistics and supporting artifacts for peer review.
- **Optionally, if the model needs to be retrained on a schedule with latest time series data, automated training is orchestrated via Airflow.**



Deploying our Models

w/ MLFlow, MLServer, and a GCS config

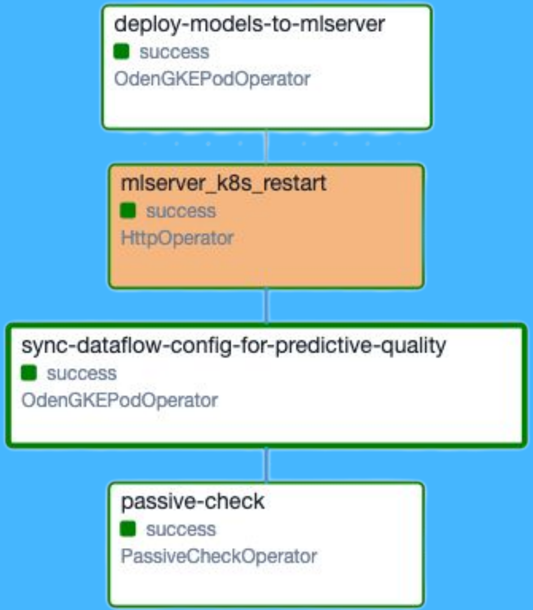
Deploying our Models

- Models in MLFlow Experiments are registered to MLFlow Model Registry along with versioning after review.

Version	Registered at
Version 17	05/20/2025, 08:42:22 AM
Version 16	05/19/2025, 03:08:29 PM
Version 15	04/22/2025, 02:09:37 PM
Version 14	02/14/2025, 11:52:12 AM
Version 13	12/06/2024, 02:09:22 PM
Version 12	12/06/2024, 11:48:07 AM
Version 11	10/19/2024, 12:54:02 PM
Version 10	10/16/2024, 11:27:55 AM
Version 9	09/25/2024, 09:55:41 AM
Version 8	09/09/2024, 02:51:15 PM

Deploying our Models

- Models in MLFlow Experiments are registered to MLFlow Model Registry along with versioning after review.
- Deploy Job is runs every hour to ensure
  - All the versioned models in Model Registry are deployed to MLServer.
  - Production model version cache/config points to the latest version



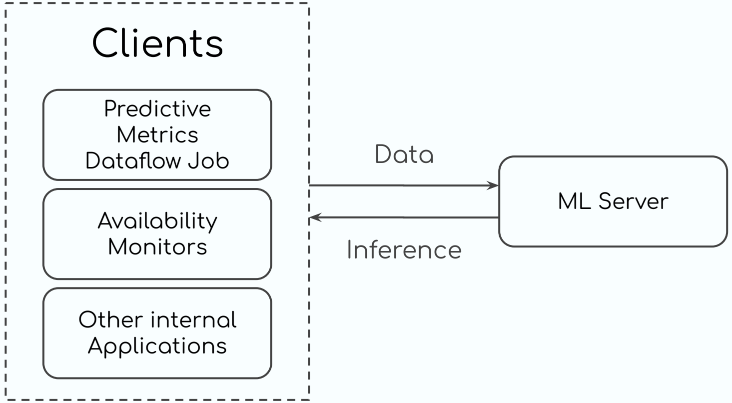
Deploying our Models

- Models in MLFlow Experiments are registered to MLFlow Model Registry along with versioning after review.
- Deploy Job is runs every hour to ensure
    - All the versioned models in Model Registry are deployed to MLServer.
    - Production model version cache/config points to the latest version
- The config contains three things
    - order of input features
    - resolution of the data expected by the model
    - Inference metric metadata


```json
{
  "input_metric_ids": [
    "3ea26934-8464-54d1-86a6-70a5c7c9a5f3",
    "99baf78a-2bdf-534f-90e5-b58fd852c2c5"
  ],
  "window_size_s": 300,
  "step_size_s": 10,
  "line_id": "613cbd00-1279-420e-b0c5-dc310b9978b9",
  "model_identifier": "Monitoring-Monitoring-Factory-Clearblade-SLO-
  "model_version": null,
  "output_metric_id": "1caee770-43b1-4813-9698-c9462e2d1de3",
  "output_device_id": "b9be0864-8a25-4260-bd84-0c90aac0c38a",
  "output_machine_id": "602edb42-9d61-42c0-869c-3897b9d040c7",
  "output_metric_name": "synthetic_predicted_metric"
}
```

Deploying our Models

- Models in MLFlow Experiments are registered to MLFlow Model Registry along with versioning after review.
- Deploy Job is runs every hour to ensure
  - All the versioned models in Model Registry are deployed to MLServer.
  - Production model version cache/config points to the latest version
- The config contains three things
  - order of input features
  - resolution of the data expected by the model
  - Inference metric metadata
- MLServer loads all the models into memory and serves inference requests from clients via GRPC

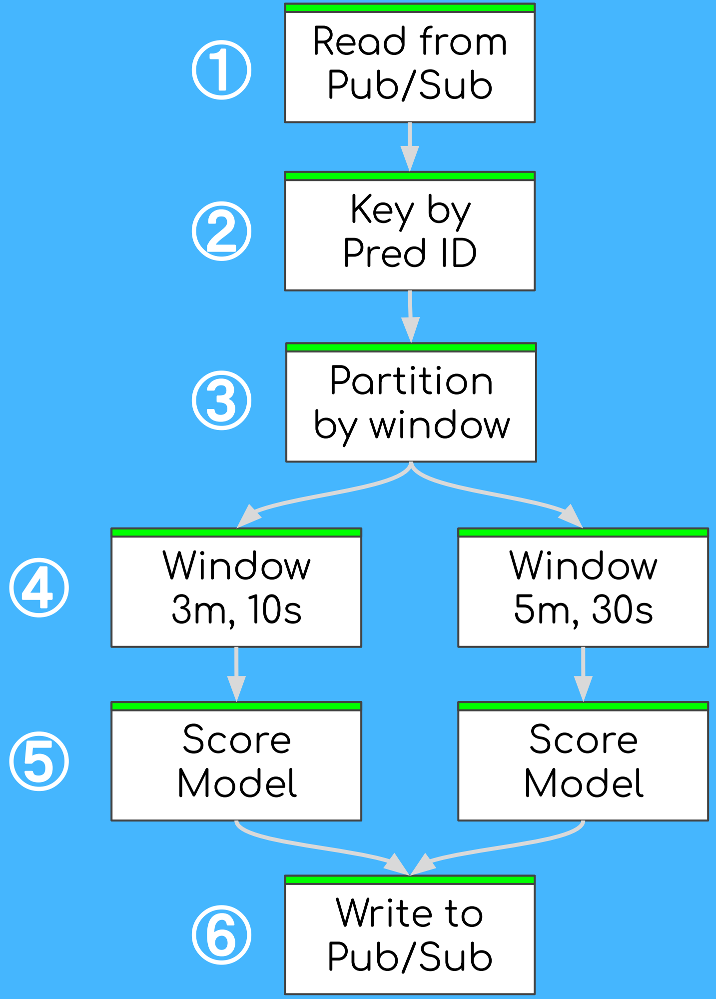


Scoring out models

With Apache Beam and MLServer

Predictive Metrics Beam Job

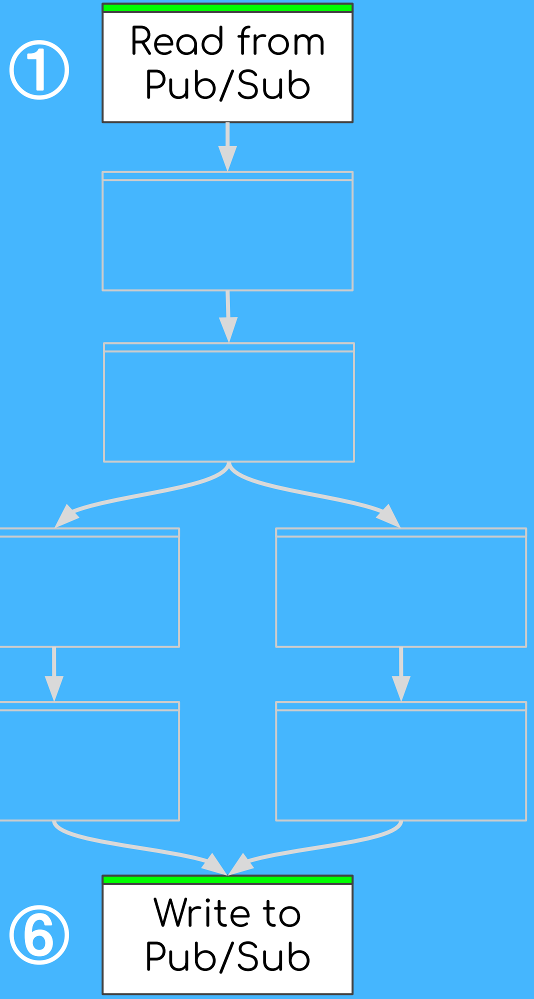
1. Read Metrics from Pub/Sub (using custom multi-source-reader)
2. Key metrics to Predictive Metric ID(s) they're components to
3. Partition key'd metrics into PCollections by windowed size+slide
4. Window by window size and slide
5. Form tensors, score model, and form new Metric object from score
6. Write new metrics to Pub/Sub (using custom multi-sink-writer)



Predictive Metrics Beam Job

- Reading and writing to Pub/Sub is done using a multi-source reader and writer.
- This allows us to deploy this job in "batch mode" via Options.

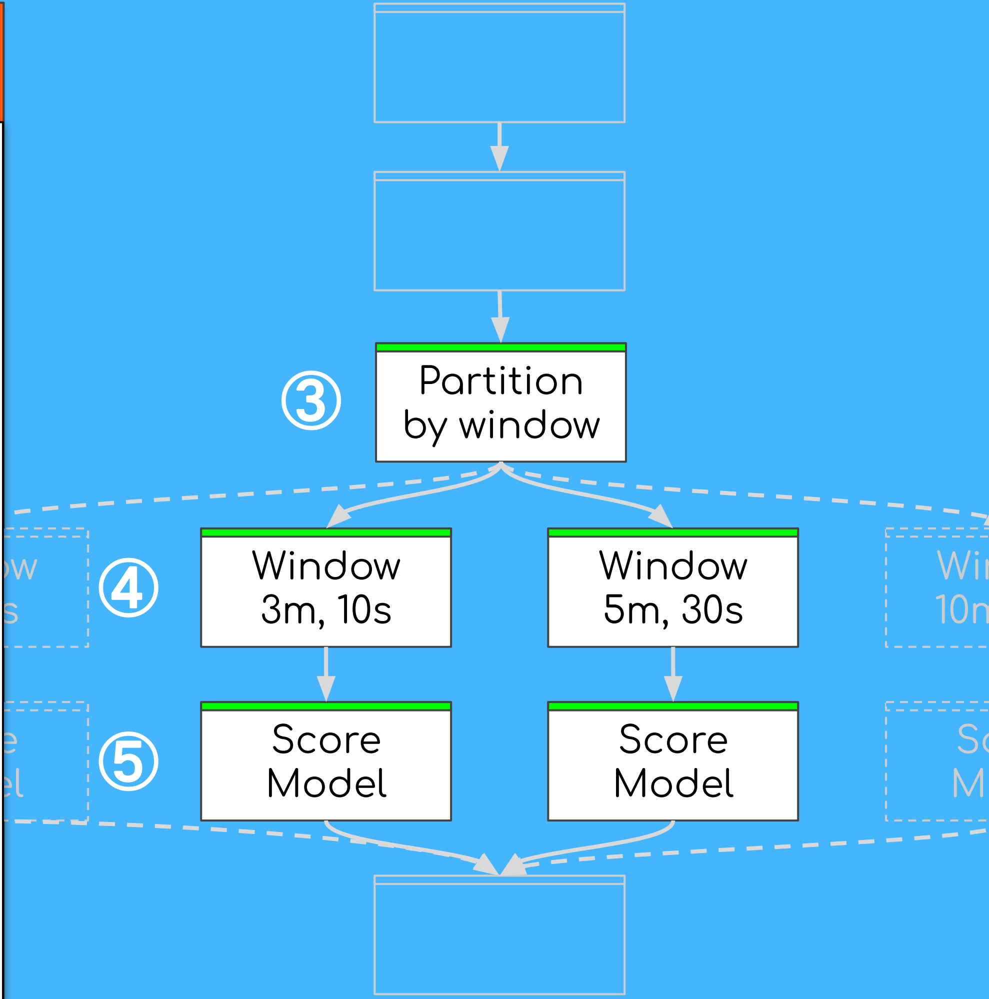
```
public static class Read<OutputT>
  extends PTransform<PBegin, PCollection<OutputT>> {

  public Read(ReadOptions options, Class<OutputT> outputClass) {...}

  public String getName() {
    return "Read " + outputClass.getSimpleName() + " from " + options.getReadMode();
  }
  ...

  public PCollection<OutputT> expand(PBegin input) {
    return switch (options.getReadMode()) {
      case "PUBSUB" -> expandPubsub(input);
      case "FILE" -> expandFile(input);
      case "BIGQUERY" -> expandBigQuery(input);
      default -> {
        throw new RuntimeException("Unknown mode: " + options.getReadMode());
...

public static class Write<InputT>
  extends PTransform<PCollection<InputT>, PDone> {

  public Write(WriteOptions options, Class<InputT> inputClass) {...}

  public String getName() {
    return "Write" + inputClass.getSimpleName() + " to " + options.getWriteMode();
  }
  ...

  public PDone expand(PCollection<AvroT> input) {
    return switch (options.getWriteMode()) {
      case "PUBSUB" -> expandPubsub(input);
      case "FILE" -> expandFile(input);
      case "FILE_WINDOWED" -> expandFileWindowed(input);
      case "LOG" -> expandLog(input);
      default -> {
        throw new RuntimeException("Unknown option: " + options.getWriteMode());
...
```



Predictive Metrics Beam Job

- Because different models are built using different sized windows, we split the pipeline by window size.
- This means window size **must be known at DAG read time** (deploy time).
- Recombining the collections with different windows is a PITA so we run just as many scoring PTransforms.
- We just build the DAG in a for-loop

```
List<PCollection<Metric>> predictiveMetricsCollections = new ArrayList<>();
int counter = 0;
for (WindowSettings window : windows) {

  TupleTag<KV<MetricKey, List<Metriquita>>> windowTag =
      allMatchedWindowTagsAsList.get(counter);
  PCollection<KV<MetricKey, List<Metriquita>>> windowedStream = splitStreams.get(windowTag);

  PCollection<Metric> predictiveMetrics =
```



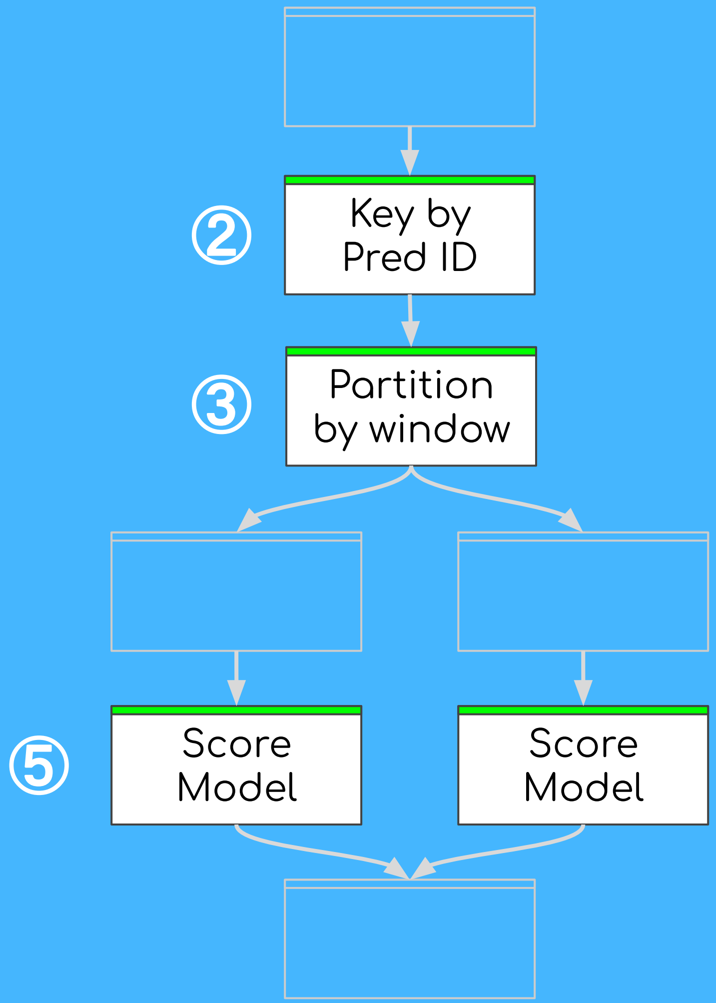
Predictive Metrics Beam Job

- Some steps require reading the **deployed model config** which is stored in GCS.

- In the past, we would:
  - Read the config on an interval using a GenerateSequence.
  - Collapse into a PCollectionView
  - Load into PTransforms as side input

- But this came with problems:
  - Cold-start issues
  - Strange PCollectionView errors

- Now our PTransforms:
  - Fetch the config from GCS when needed.
  - Cache in the PTransform w/ TTL



Predictive Metrics Beam Job

- Some steps require reading the **deployed model config** which is stored in GCS.
- In the past, we would:
  - Read the config on an interval using a GenerateSequence.
  - Collapse into a PCollectionView
  - Load into PTransforms as side input
- But this came with problems:
  - Cold-start issues
  - Strange PCollectionView errors
- Now our PTransforms:
  - Fetch the config from GCS when needed.
  - Cache in the PTransform w/ TTL

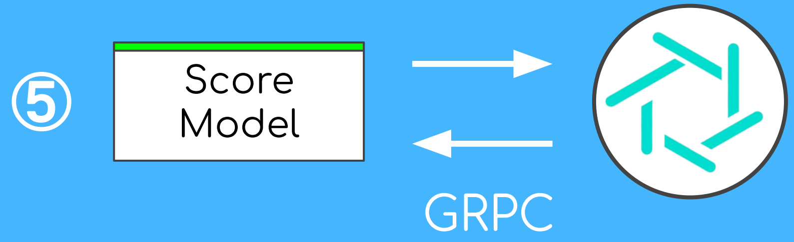
```
/**
 * A base DoFn that encapsulates the logic for fetching configuration from GCS and refreshing
 * definitions.
 */
4 inheritors
public abstract static class ConfigDoFn<InputT, OutputT> extends DoFn<InputT, OutputT> {

  // The static Storage handle is shared among all subclasses
  private static final Storage storage = StorageOptions.getDefaultInstance().getService();

  protected final String bucketName;
  protected final String objectName;

  protected TimedGCSFetcher fetcher;
  protected PredictiveMetricDefinitions definitions;

  public ConfigDoFn(String bucketName, String objectName) {
    this.bucketName = bucketName;
    this.objectName = objectName;
  }

  public static void refreshDefinitions(
      TimedGCSFetcher fetcher, PredictiveMetricDefinitions definitions)
      throws MissingConfigurationException {
    fetcher.refresh();
    if (definitions.neverSucceeded()) {
      LOG.error("No predictive metric definitions present");
      throw new MissingConfigurationException("No predictive metric configuration present");
    }
  }

  1 override
  @Setup
  public void setup()
      throws MissingConfigurationException, TextFormat.ParseException, InvalidFormatException {
    this.definitions = new PredictiveMetricDefinitions();
    this.fetcher = new TimedGCSFetcher(storage, bucketName, objectName, this.definitions);
    refreshDefinitions(fetcher, definitions);
  }

  @StartBundle
  public void startBundle(StartBundleContext context) throws MissingConfigurationException {
    refreshDefinitions(fetcher, definitions);
  }
}
```

Scoring w/ MLServer

- MLServer is an application for serving standard inference runtimes via REST and GRPC
- Serves models over the **Open Inference Protocol** standard for scoring
- Lets users serve multiple models at once (multi-modal serving)

Why not Vertex?

- Vertex requires packaging each model in it's own container meaning more isolation but more resources per model.
- At the time we chose MLServer, Vertex required one vCPU per model.



Embedded Model Scoring

- **Pro:** Low latency, no external calls, easy to parallelize.
- **Pro:** Data Scientists will touch Python.
- **Pro:** Built-in RunInference transform.
- **Con:** In our experience, Python Beam streaming is less performant at windowing.
- **Con:** We have lots of homegrown code for writing Java Beam jobs.
- **Considered:** Multi-Language pipelines but we have no operational experience in these.

External Scoring Service

- **Pro:** We get to use Java.
- **Pro:** It's easy to test and scale scoring our models from non-beam (APIs).
- **Pro:** We've decoupled model scoring dependencies from pybeam dependencies.
- **Pro:** All model scoring exists in only one place.
- **Con:** We risk being IO-bound.
- **Con:** Error tracking is more difficult.

Scoring against MLServer

Scoring w/ MLServer is easy:

1. Sort our input values by their ID.

```
// Sort the metrics by their metricID
HashMap<String, List<Metriquita>> metricsByMetricId = new HashMap<>();
for (Metriquita metric : metrics) {
  if (!metricsByMetricId.containsKey(metric.getMetricId())) {
    metricsByMetricId.put(metric.getMetricId(), new ArrayList<>());
  }
  metricsByMetricId.get(metric.getMetricId()).add(metric);
}
```

2. Form our (2d) tensor:

```
// Create a tensor from the metrics (num_metrics, window_size)
double[][] tensor = new double[numExpectedInputMetrics][definition.getWindowSizeS()];
for (int i = 0; i < numExpectedInputMetrics; i++) {
  String metricId = definition.getInputMetricIds()[i];
  List<Metriquita> metricList = metricsByMetricId.get(metricId);
  for (int j = 0; j < definition.getWindowSizeS(); j++) {
    tensor[i][j] = metricList.get(j).getValue();
  }
}
```

3. And score via GRPC

```
ModelInferRequest request =
    ModelInferRequest.newBuilder()
        .setModelName(definition.getModelIdentifier())
        .setModelVersion(Integer.toString(definition.getModelVersion()))
        .addInputs(
            ModelInferRequest.InferInputTensor.newBuilder()
                .setName("input-0")
                .setDatatype("FP64")
                .addAllShape(List.of(-1L, (long) tensor.length, (long) tensor[0].length))
                .setContents(
                    InferTensorContents.newBuilder()
                        .addAllFp64Contents(
                            Arrays.stream(tensor) Stream<double[]>
                                .flatMapToDouble(Arrays::stream) DoubleStream
                                .boxed() Stream<Double>
                                .collect(Collectors.toList()))
                        .build())
                .build())
        .build();

ModelInferResponse resp;
int retries = 3;
StatusRuntimeException lastException = null;
while (retries > 0) {
  try {
    resp = this.client.modelInfer(request);
    return resp.getOutputs( index: 0).getContents().getFp64Contents( index: 0);
  } catch (StatusRuntimeException e) {
    // If it's an issue with the request, don't retry.
    if (!GRPCErrorHandler.shouldRetryOnError(e)) return null;
    LOG.warn("Failed to score tensor, try {} of {}", RETRIES - retries + 1, RETRIES, e);
    lastException = e;
    retries--;
    try {
      Thread.sleep((long) (SLEEP_MS * Math.pow(RETRIES - retries, 2)));
    } catch (InterruptedException ex) {
      Thread.currentThread().interrupt();
    }
  }
}
throw lastException;
```

After v1

Some interesting challenges along the way.

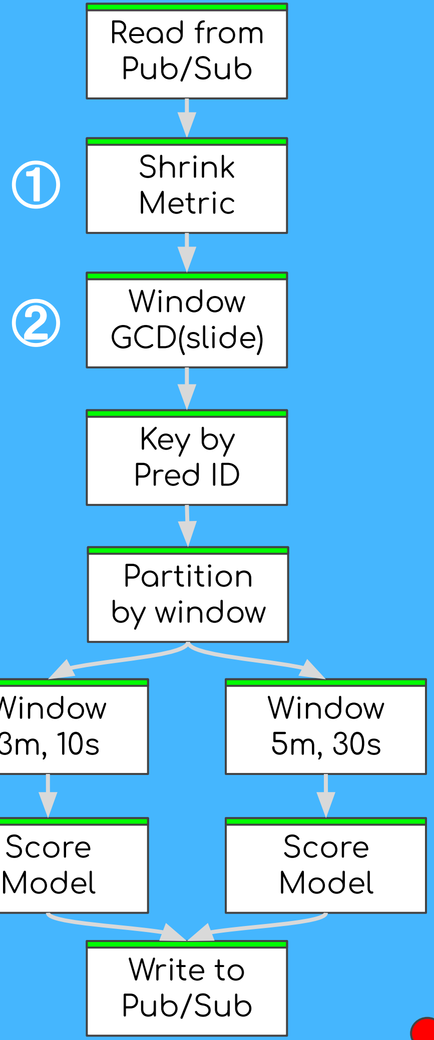
Streaming Engine Optimization

Due to the high dimensionality of the windowed join (num_inputs * window_size / window_slide) Streaming Engine was the largest cost driver of our models making them unprofitable for contracts ($1,300 to 1,800 per model per year).

To solve this, we added two steps:

1. Shrink the (serialized) metric as much as possible.

2. Window in two-stages.



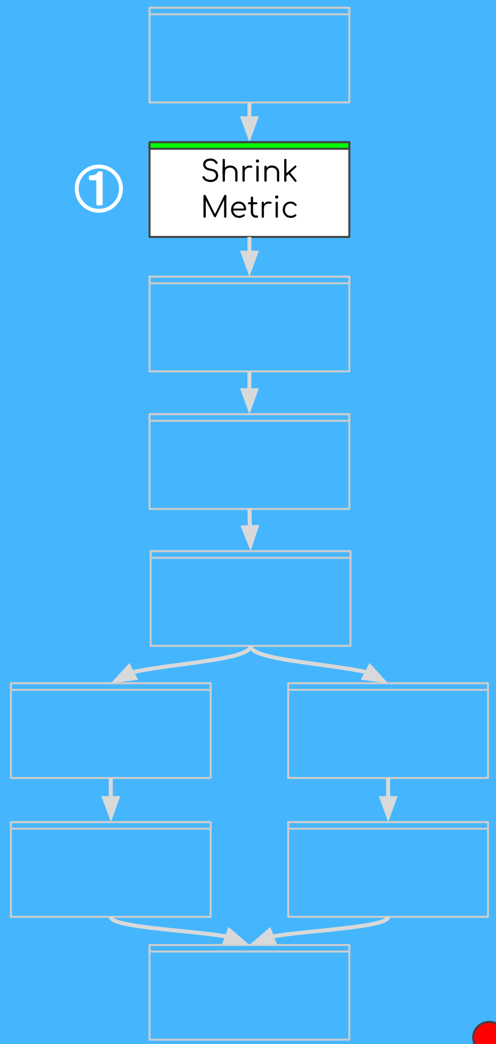
Streaming Engine Optimization

Previously, our Metric class:

- Irrelevant UUIDs that were stored as 36-char strings.
- A legacy “name” identifier.
- Serialized using SchemaCoder (which is way better than Serializable!)

We introduced a new smaller Metric class (Metriquita) which:

- Dropped everything but the metric UUID, value, and timestamp.
- Used a CustomCoder to tightly pack the UUIDs as two longs.



Streaming Engine Optimization

```
public class MetriquitaCoder extends CustomCoder<Metriquita> {
  private static final MetriquitaCoder INSTANCE = new MetriquitaCoder();
  private MetriquitaCoder() {}
  public static MetriquitaCoder of() { return INSTANCE; }

  @Override
  public void encode(Metriquita value, OutputStream outStream) throws IOException {
    DataOutputStream dataOut = new DataOutputStream(outStream);
    dataOut.writeLong(value.metricIdMostSigBits);
    dataOut.writeLong(value.metricIdLeastSigBits);
    dataOut.writeLong(value.timestampMs);
    dataOut.writeDouble(value.value);
  }

  @Override
  public Metriquita decode(InputStream inStream) throws IOException {
    DataInputStream dataIn = new DataInputStream(inStream);
    Metriquita record = new Metriquita();
    record.metricIdMostSigBits = dataIn.readLong();
    record.metricIdLeastSigBits = dataIn.readLong();
    record.timestampMs = dataIn.readLong();
    record.value = dataIn.readDouble();
    return record;
  }
}
```

```
SchemaCoder is: 138
SerializableCoder is: 334
SnappyCoder is: 144
MetriquitaCoder is: 32
```

Streaming Engine Optimization

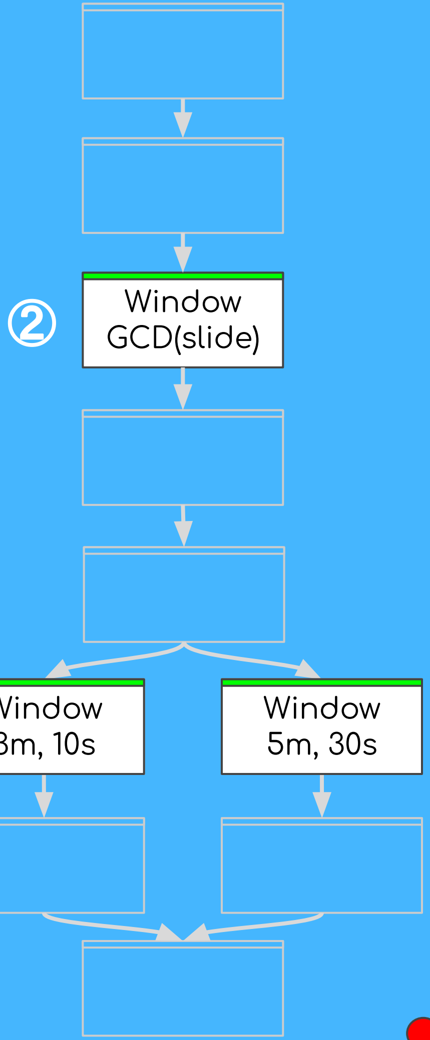
Metriquita reduced each element by a constant 106b. But we still had to account for:

- Pairing a key to each element (+38b)
- Adding the window to each pair (**+300b**)

The clear target was to **reduce the number of elements joined in a window once** and, unintuitively, this was accomplished by **windowing twice.**

Window 1: Pre-aggregate each metric into a list of metrics (GCD of all possible window slides)

Window 2: Normal windowing but now with small list-chunks of input metrics.



```
seconds_in_a_day / window_step_size_s * num_input_metrics * window_size_s * 384b
```

```
seconds_in_a_day / window_step_size_s * num_input_metrics * window_size_s * 384b
```

Joins per day — Elements to join — Element size

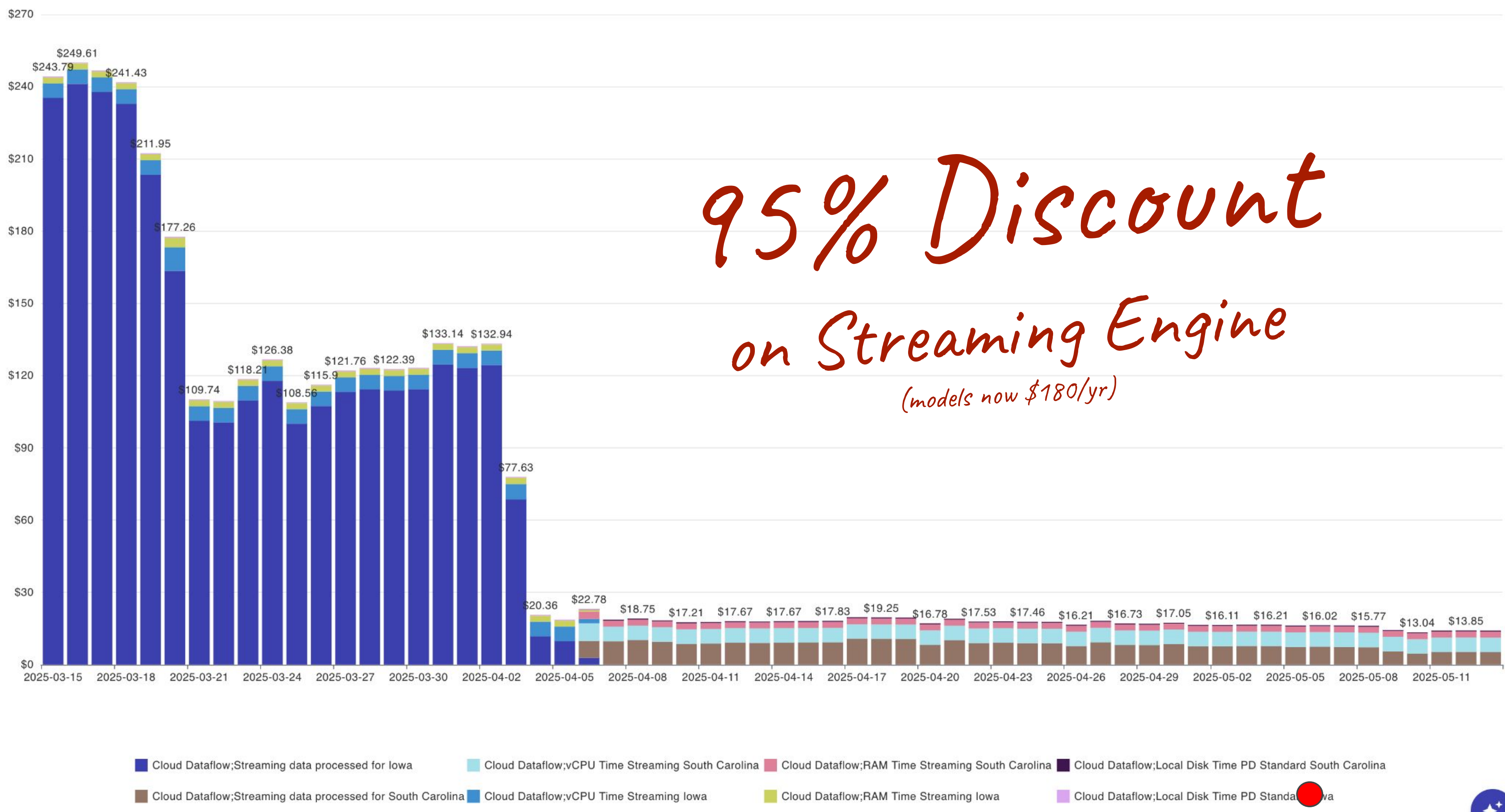
```
seconds_in_a_day / window_step_size_s * num_input_metrics * 384b
+
seconds_in_a_day / window_step_size_s * window_size_s / gcd_slides * num_input_metrics * 658b
```

```
seconds_in_a_day / window_step_size_s * num_input_metrics * 384b
```

Joins per day (first) — Elements to join (first) — Element Size (first)

```
+ seconds_in_a_day / window_step_size_s * window_size_s / gcd_slides * num_input_metrics * 658b
```

Joins per day (second) — Lists to join (second) — List Size (second)

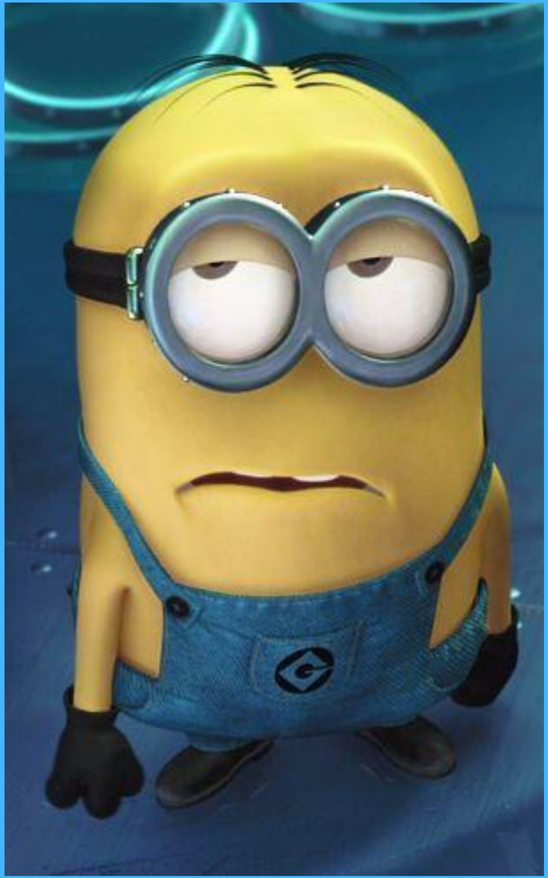

95% Discount
on Streaming Engine
(models now $180/yr)
$270
$240
$210
$180
$150
$120
$90
$60
$30
$0
$243.79
$249.61
$241.43
$211.95
$177.26
$109.74
$118.21
$126.38
$108.56
$115.9
$121.76
$122.39
$133.14
$132.94
$77.63
$20.36
$22.78
$18.75
$17.21
$17.67
$17.67
$17.83
$19.25
$16.78
$17.53
$17.46
$16.21
$16.73
$17.05
$16.11
$16.21
$16.02
$15.77
$13.04
$13.85
2025-03-15
2025-03-18
2025-03-21
2025-03-24
2025-03-27
2025-03-30
2025-04-02
2025-04-05
2025-04-08
2025-04-11
2025-04-14
2025-04-17
2025-04-20
2025-04-23
2025-04-26
2025-04-29
2025-05-02
2025-05-05
2025-05-08
2025-05-11
Cloud Dataflow;Streaming data processed for Iowa
Cloud Dataflow;vCPU Time Streaming South Carolina
Cloud Dataflow;RAM Time Streaming South Carolina
Cloud Dataflow;Local Disk Time PD Standard South Carolina
Cloud Dataflow;Streaming data processed for South Carolina
Cloud Dataflow;vCPU Time Streaming Iowa
Cloud Dataflow;RAM Time Streaming Iowa
Cloud Dataflow;Local Disk Time PD Standa

Shared Inference Resources

- At Oden, we have a large number of tiny models. Resource sharing by models is crucial for cost scaling reasons.
  - 4 cpu cores and 4 gigs of memory
  - 150+ production sklearn pipelines
  - 350 req/minute with <200ms latency

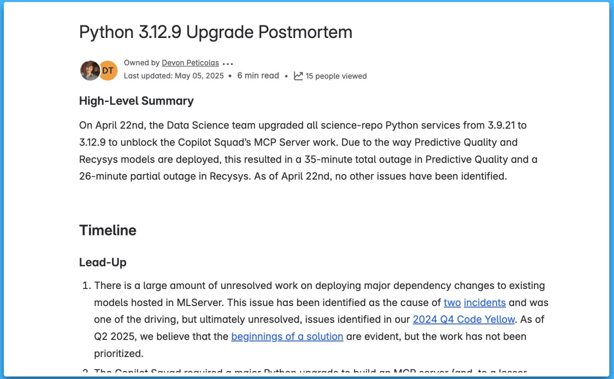
Shared Inference Resources

- At Oden, we have a large number of tiny models. Resource sharing by models is crucial for cost scaling reasons.
    - 4 cpu cores and 4 gigs of memory
    - 150+ production sklearn pipelines
    - 350 req/minute with <200ms latency
- But we are restricted to a single python runtime!!



Shared Inference Resources

- At Oden, we have a large number of tiny models. Resource sharing by models is crucial for cost scaling reasons.
  - 4 cpu cores and 4 gigs of memory
  - 150+ production sklearn pipelines
  - 350 req/minute with <200ms latency
- But we are restricted to a single python runtime!!
  - Changes in code for new models may break already existing models
  - Python upgrade needed careful planning and gymnastics
    - Perform a surgery OR
    - Retrain models in new runtime



Python 3.12.9 Upgrade Postmortem

Owned by Devon Peticolas ...
Last updated: May 05, 2025 • 6 min read • 15 people viewed

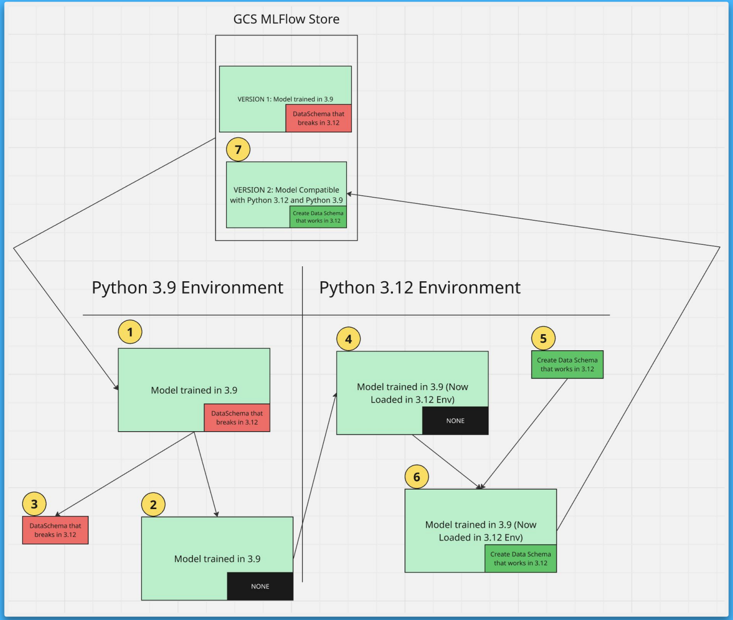
High-Level Summary

On April 22nd, the Data Science team upgraded all science-repo Python services from 3.9.21 to 3.12.9 to unblock the Copilot Squad's MCP Server work. Due to the way Predictive Quality and Recysys models are deployed, this resulted in a 35-minute total outage in Predictive Quality and a 26-minute partial outage in Recysys. As of April 22nd, no other issues have been identified.

Timeline

Lead-Up

1. There is a large amount of unresolved work on deploying major dependency changes to existing models hosted in MLServer. This issue has been identified as the cause of two incidents and was one of the driving, but ultimately unresolved, issues identified in our 2024 Q4 Code Yellow. As of Q2 2025, we believe that the beginnings of a solution are evident, but the work has not been prioritized.



In Conclusion

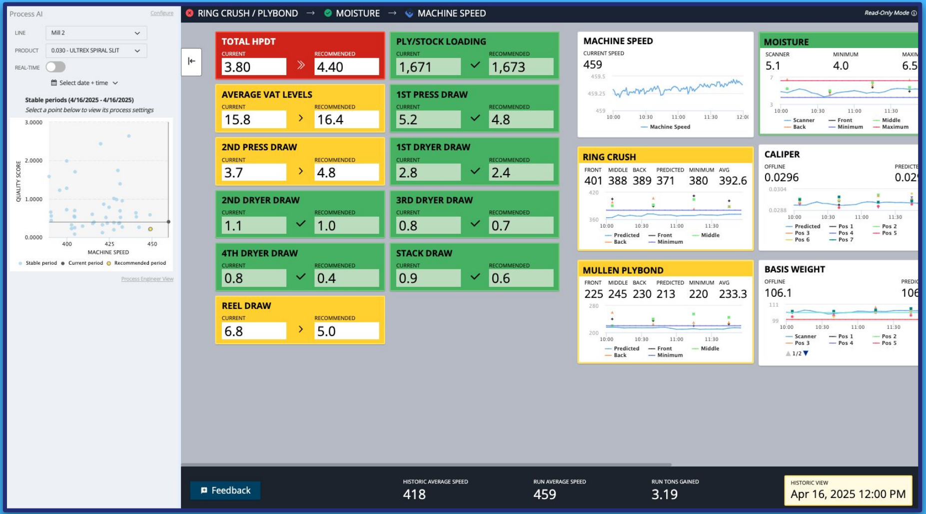
Takeaways

- Streaming Beam works well forming and scoring windows of data!
  - We needed to pay close attention to Streaming Engine costs on Dataflow.
  - It's worth testing your encoders!
  - Syncing MLServer and Dataflow via a simple JSON config has been easier than anticipated!
- Using an external service for scoring was a good call!
  - IO was never an issue.
  - Opened up non-beam inference capabilities.
- We're still struggling to balance cost vs runtime.
  - A single inference server and runtime has saved us money.
  - Shared dependencies makes model deployment stressful.
- MLFlow and MLServer have allowed easy experimentation and deployment by Data Scientists.

Where are we going?

- Many models perform well in real-time! 95% correlation, >60% R^2
- Some offline quality tests are harder to model than others.
- Large inconsistencies in the models between products being manufactured.

- **We are seeing success embedding our quality predictions in bigger systems.**
- Now that we've built this infrastructure we can explore other predictive models such as predicting future in-line metrics.



Devon and Jeswanth

QUESTIONS?

BEAM SUMMIT NYC 2025

devon@oden.io
jeswanth.yadagani@oden.io