

FOA 1861 FINAL PROJECT BRIEFING

BIG DATA ANALYSIS OF SYNCHROPHASOR DATA

Combinatorial Evaluation of Physical Feature Engineering, Classical Machine Learning, and Deep Learning Models for Synchrophasor Data at Scale

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PingThings

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Project Partners



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Outline

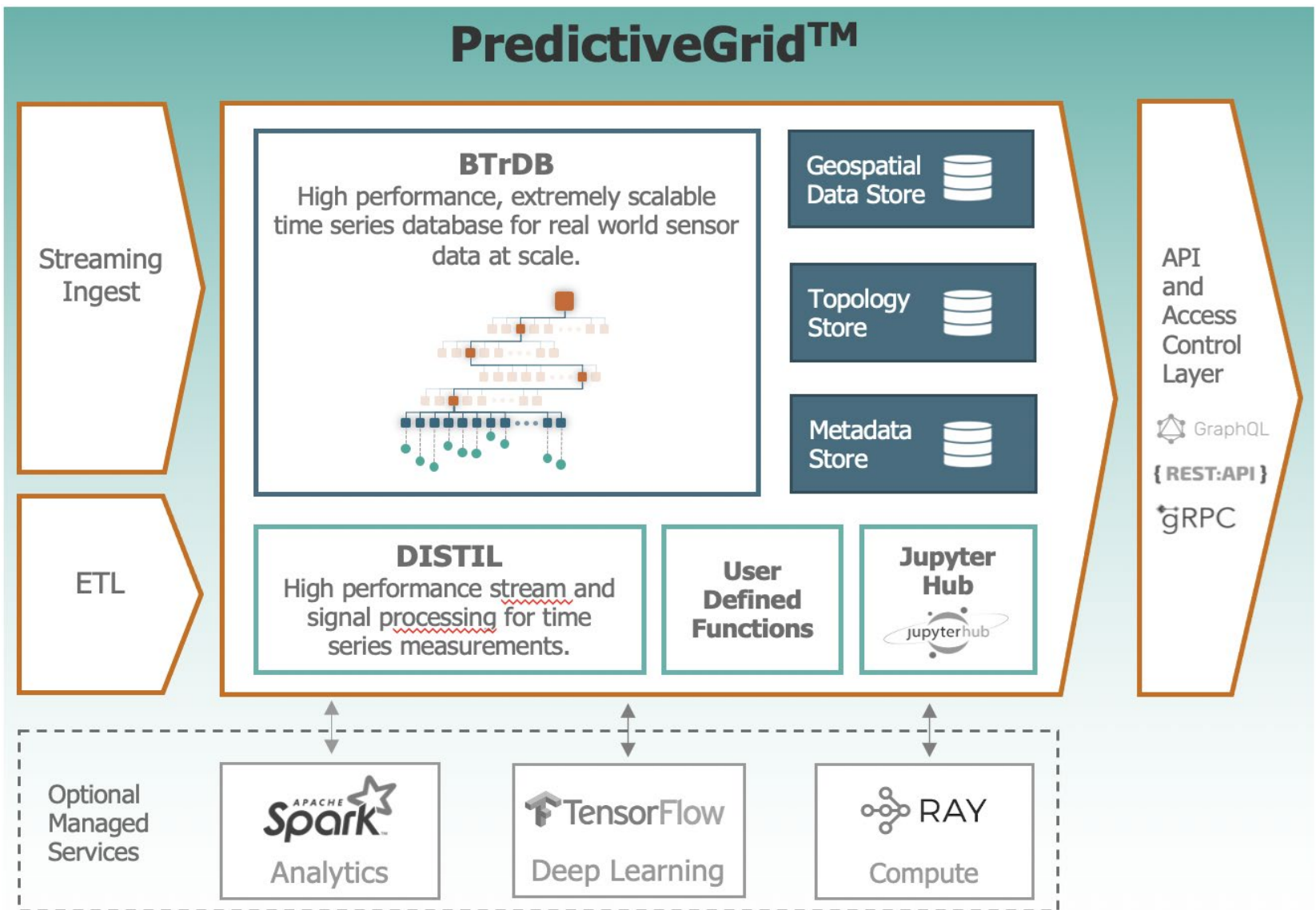
- Background
- Experimental Results
 - Statistical & ML Pipeline
 - Assessment of Datasets
 - Validation Results
- Technical Accomplishments
- Value of Work
- Readiness for Commercialization
- Readiness for ML & BD Analytics
- Lessons Learned and Next Steps



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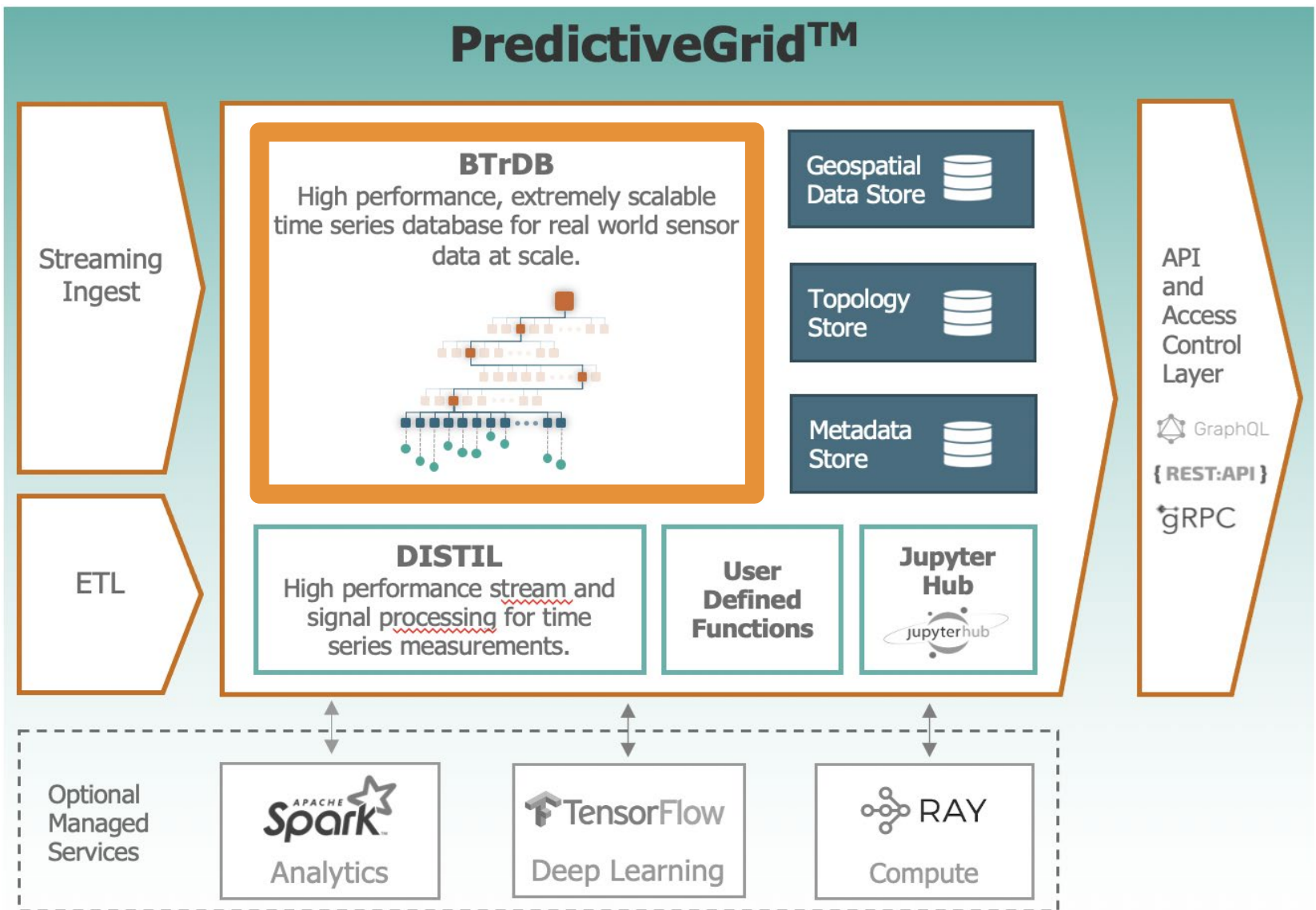
Background - The Platform



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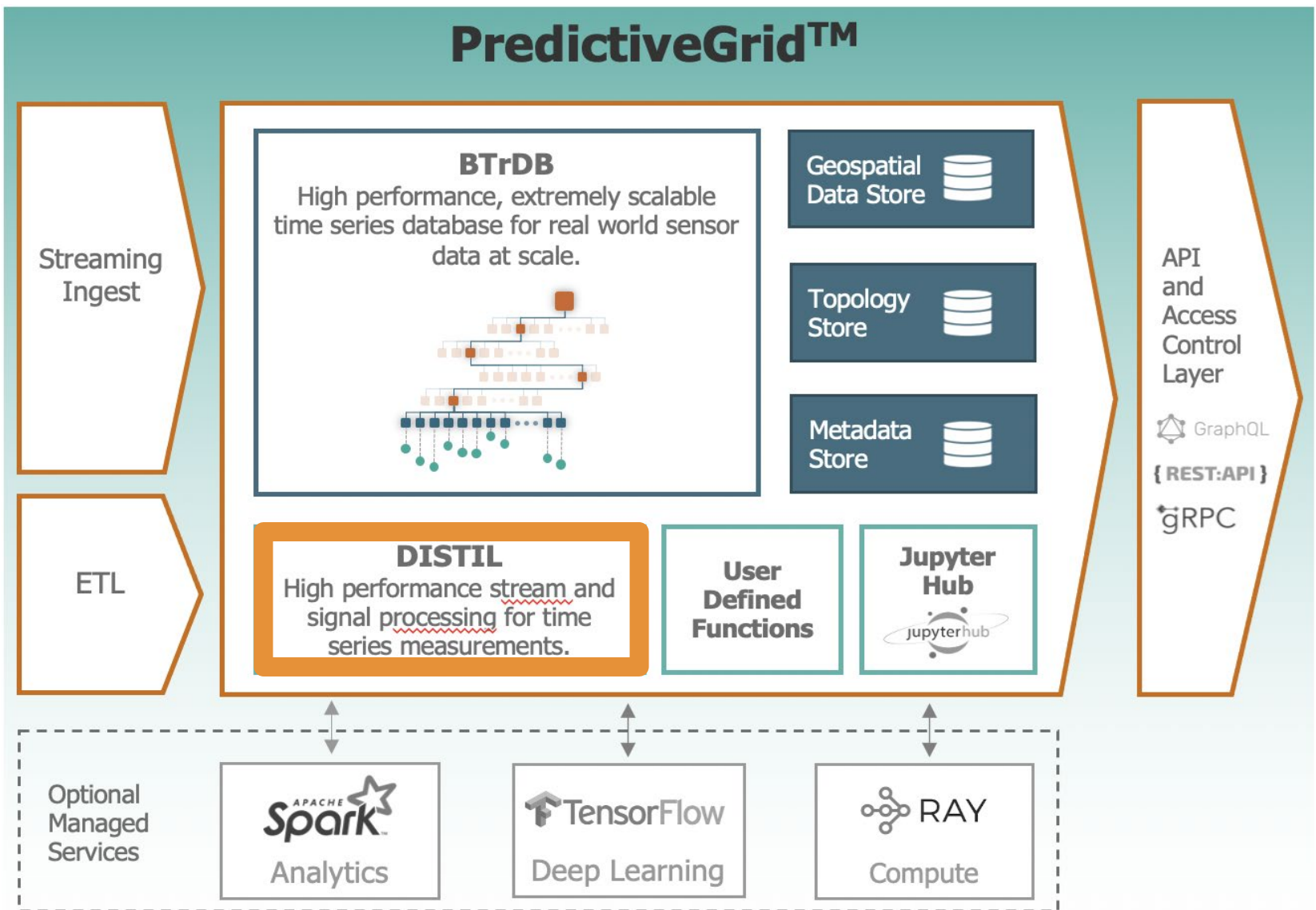
Background - The Platform



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Background - The Platform



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Background - Our Approach

Aims

- Identify & classify events (within and outside utility logs)
- Identify & classify precursors
- Extract event signatures
- Discover seasonal & weather patterns

Strategy

- Broad survey & assessment of algorithms for these tasks.

Significance

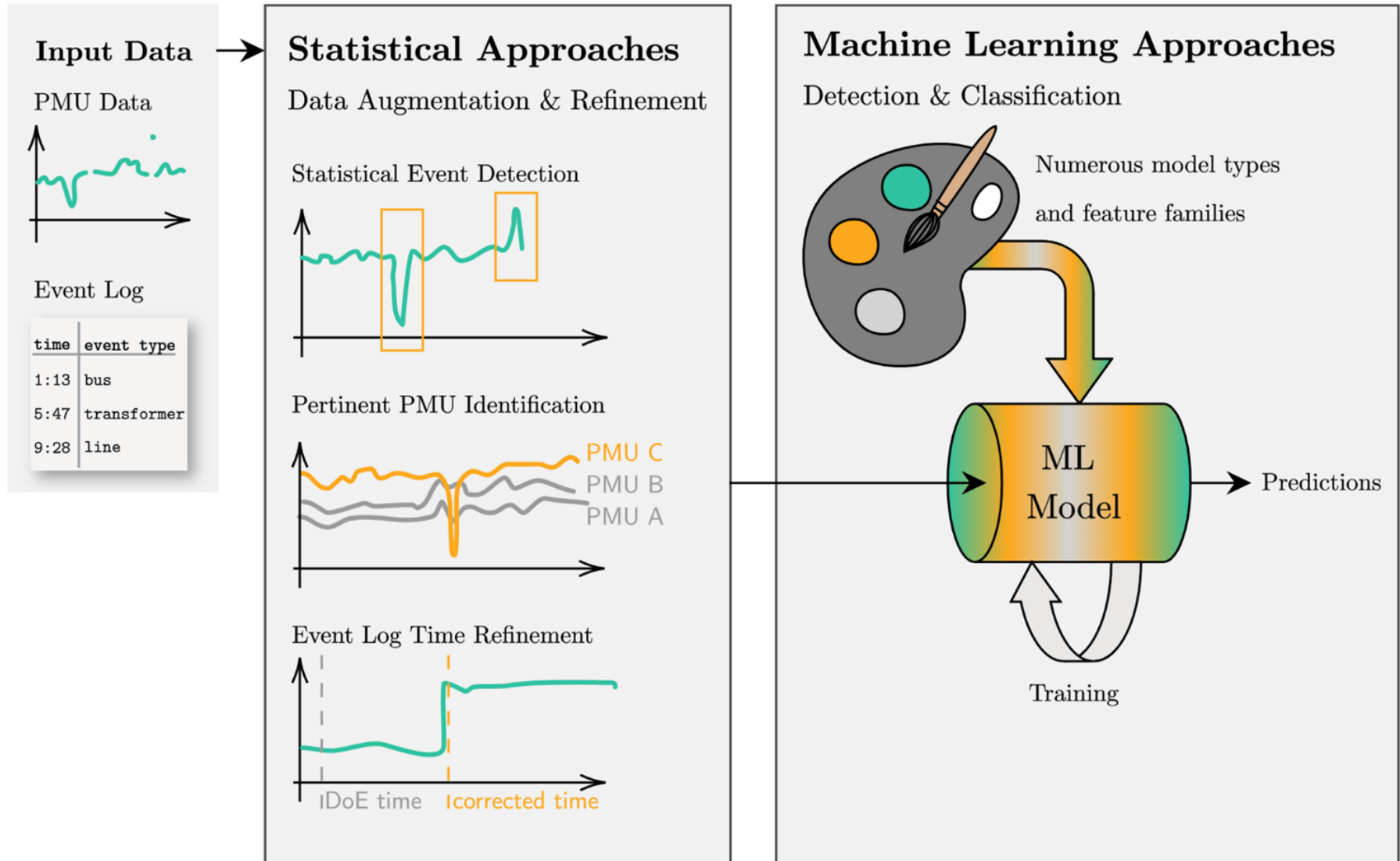
- Development of broadly useful tooling for pain free analytics pipeline.
- Algorithm discoveries



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Statistical & ML Pipeline



Dataset Assessment

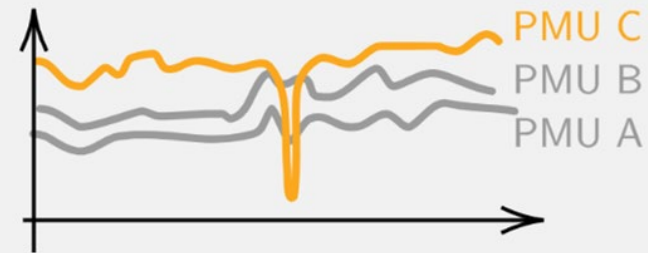
Measurements

- Missing measurements
- Bad values
- Mislabeling

Event Logs

- Event times inaccurate
- No spatial information - topology or event location

Pertinent PMU Identification



Event Log Time Refinement

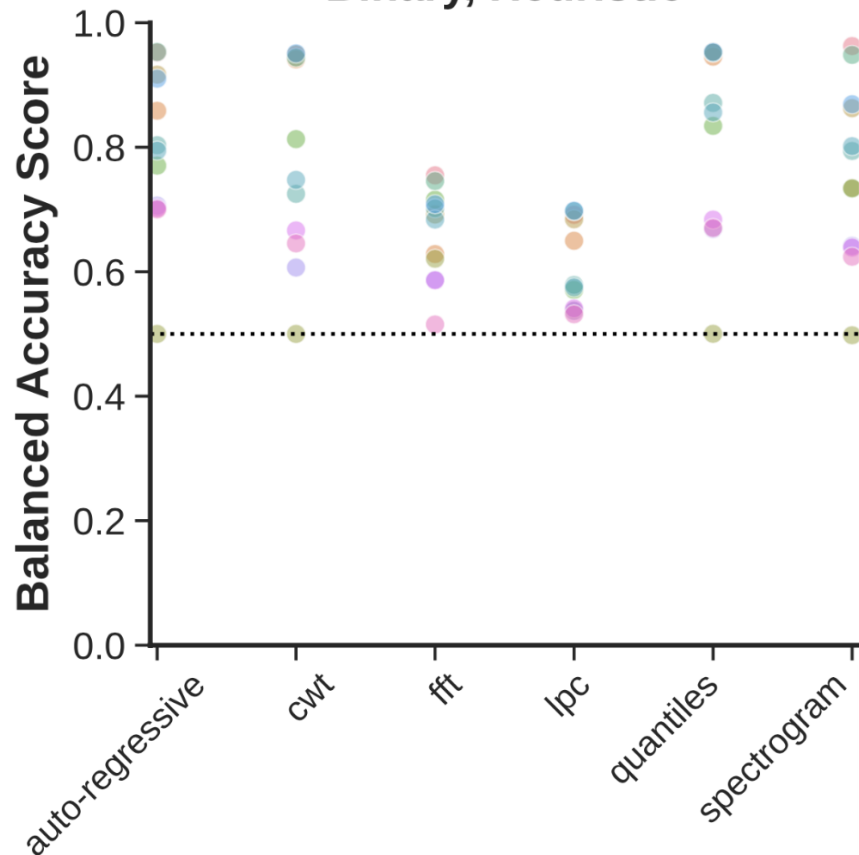


Validation Results

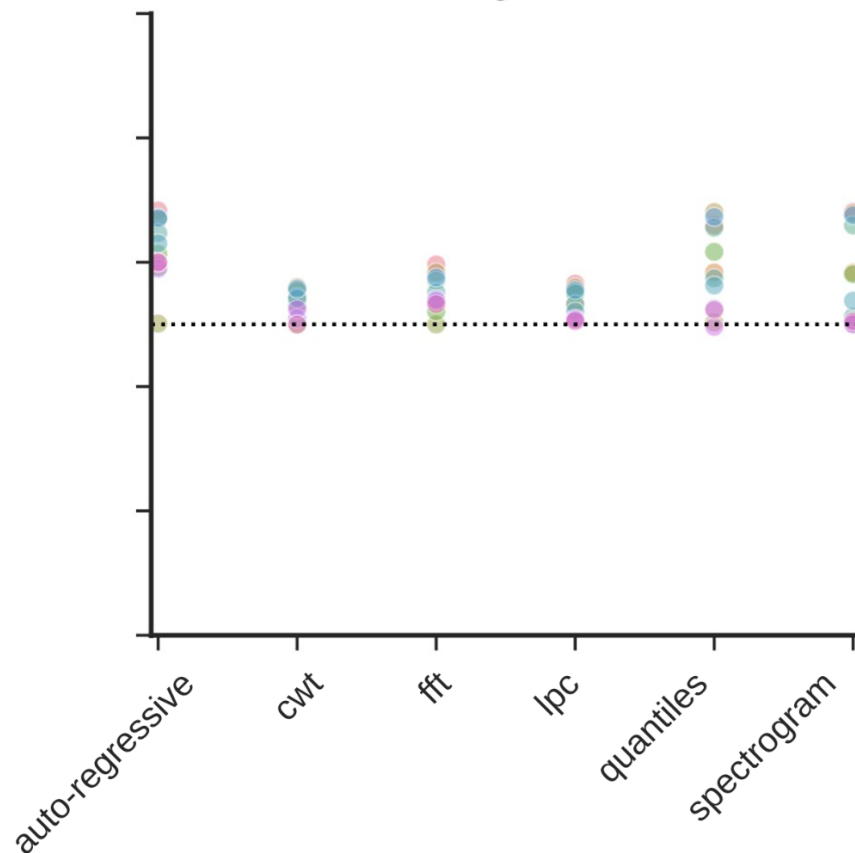
Event Detection & Classification

- estimator
- CatBoostClassifier
 - DecisionTreeClassifier
 - ExtraTreesClassifier
 - GaussianNB
 - KNeighborsClassifier
 - LGBMClassifier
 - MLPClassifier
 - MLPDeepClassifier
 - RandomForestClassifier
 - SGDClassifier-hinge
 - SGDClassifier-log
 - SGDClassifier-modified_huber

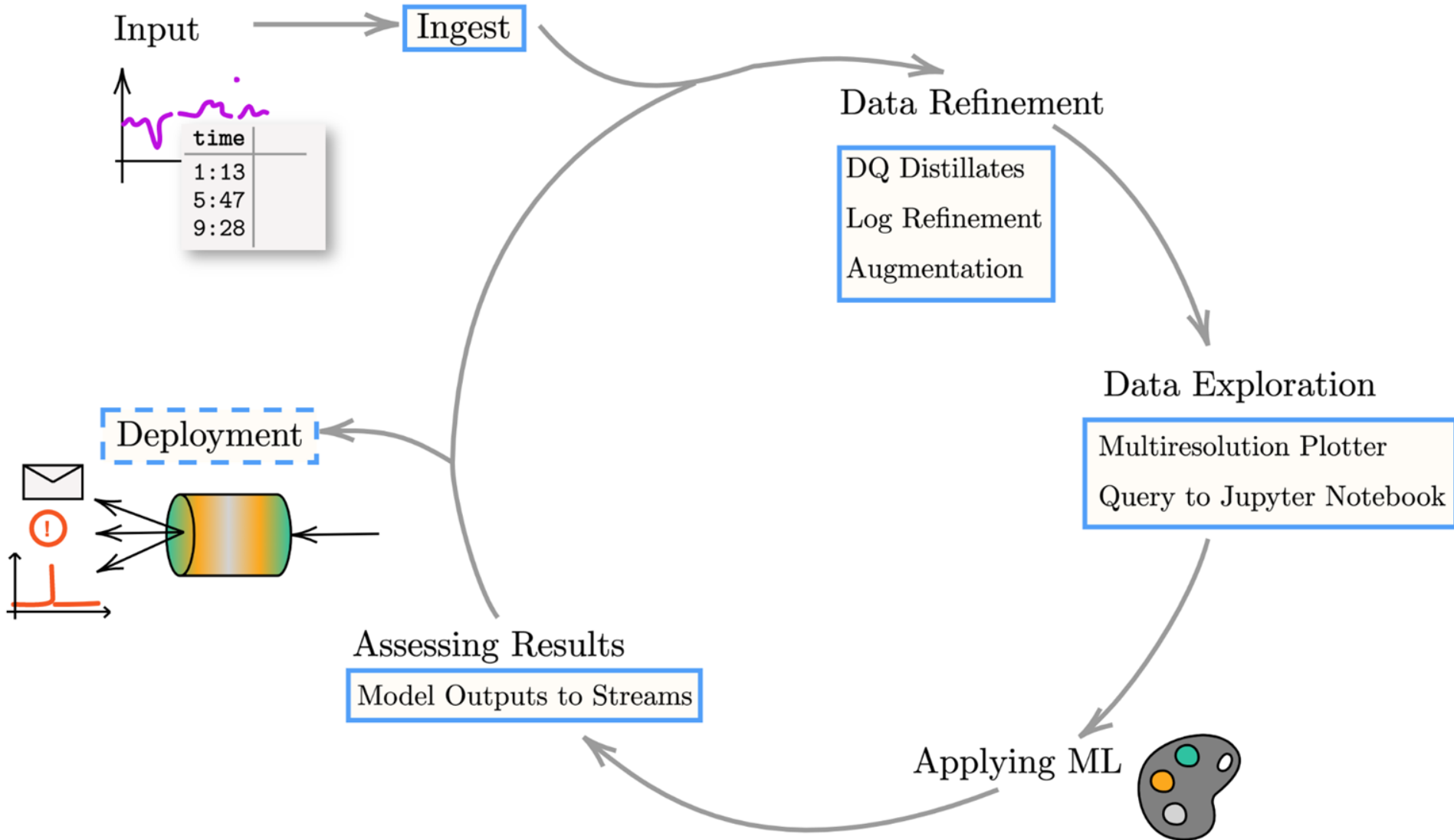
Binary, Heuristic



Binary, DoE



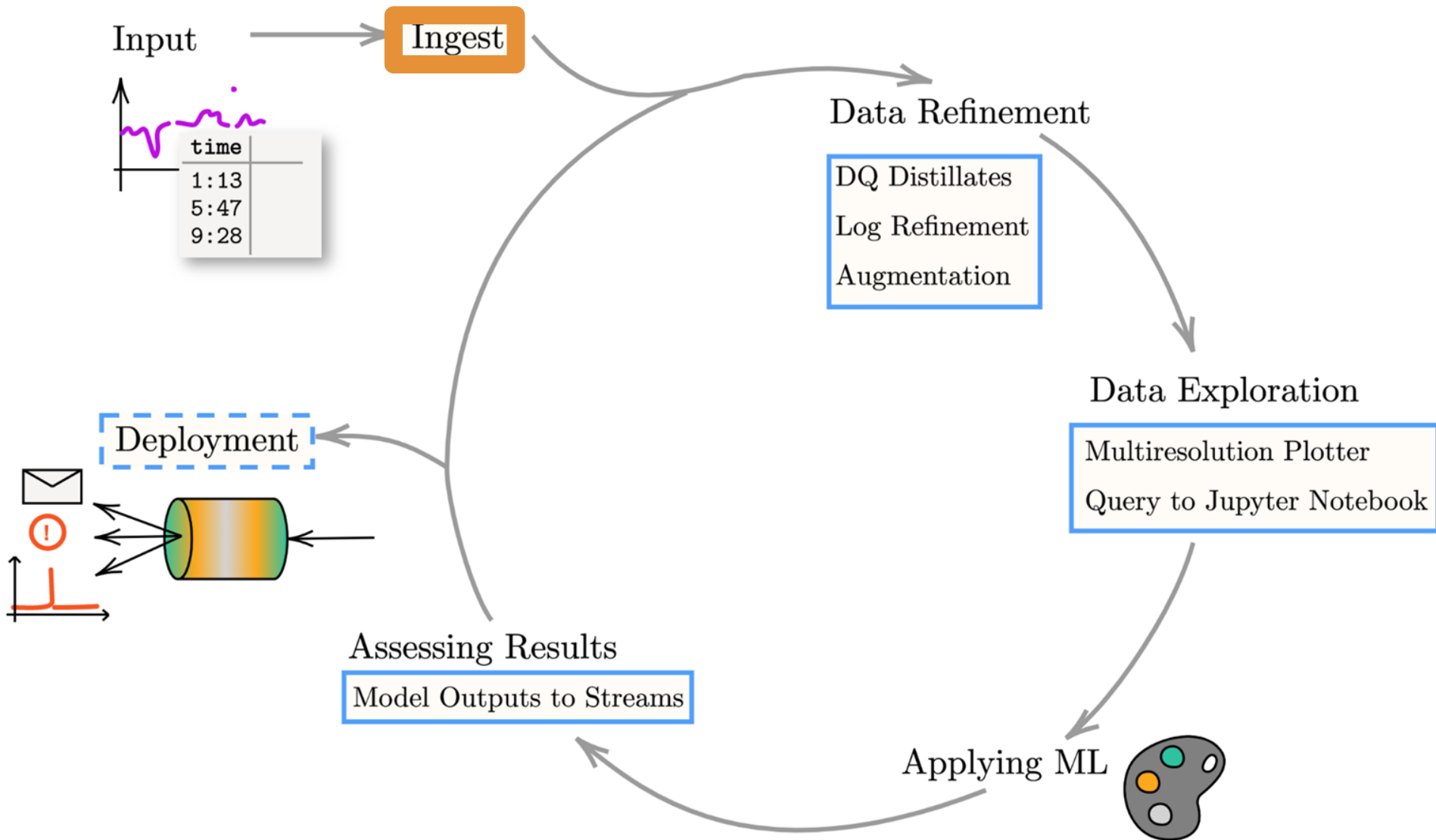
An AI Platform for Grid Data



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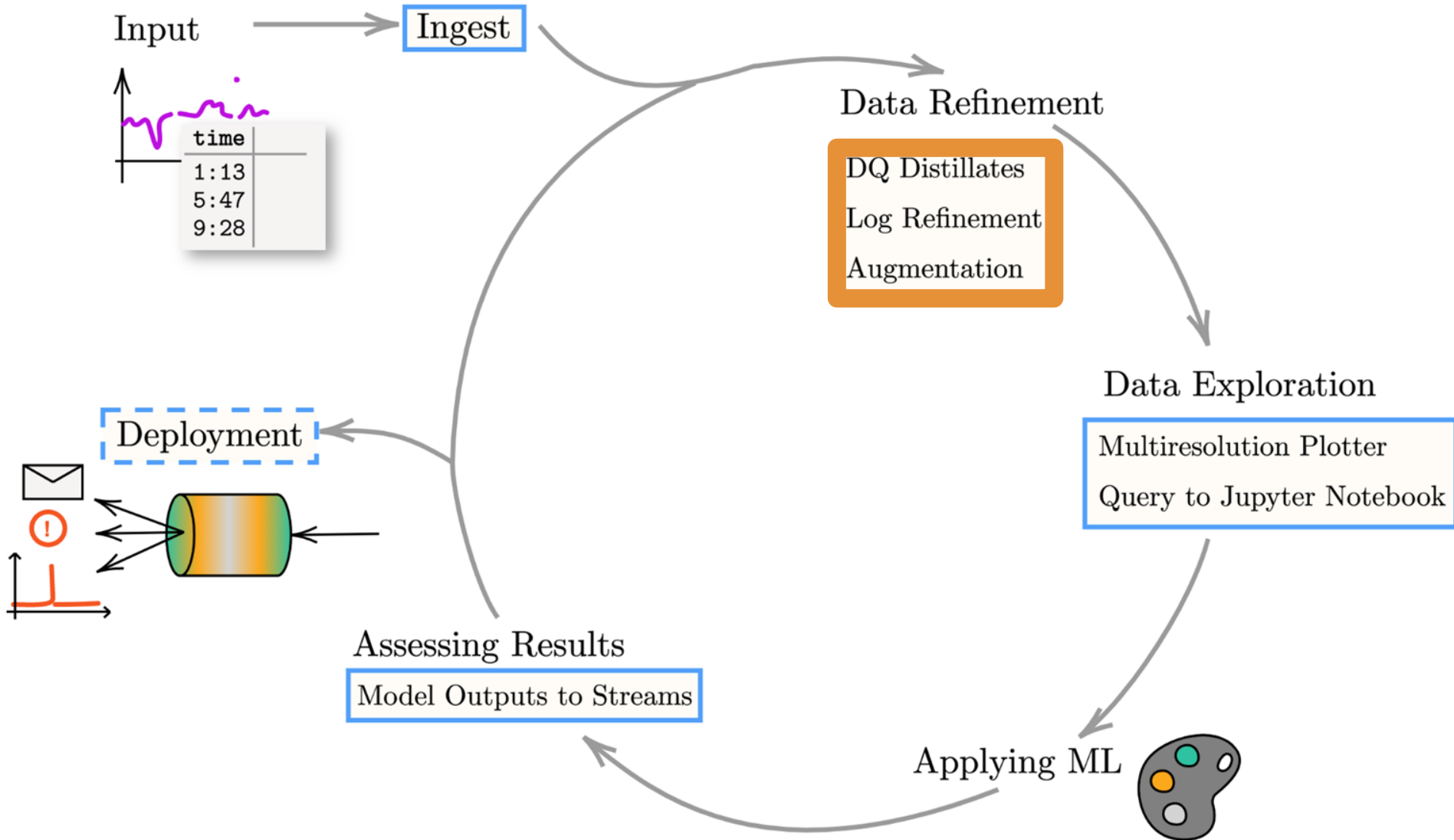
An AI Platform for Grid Data



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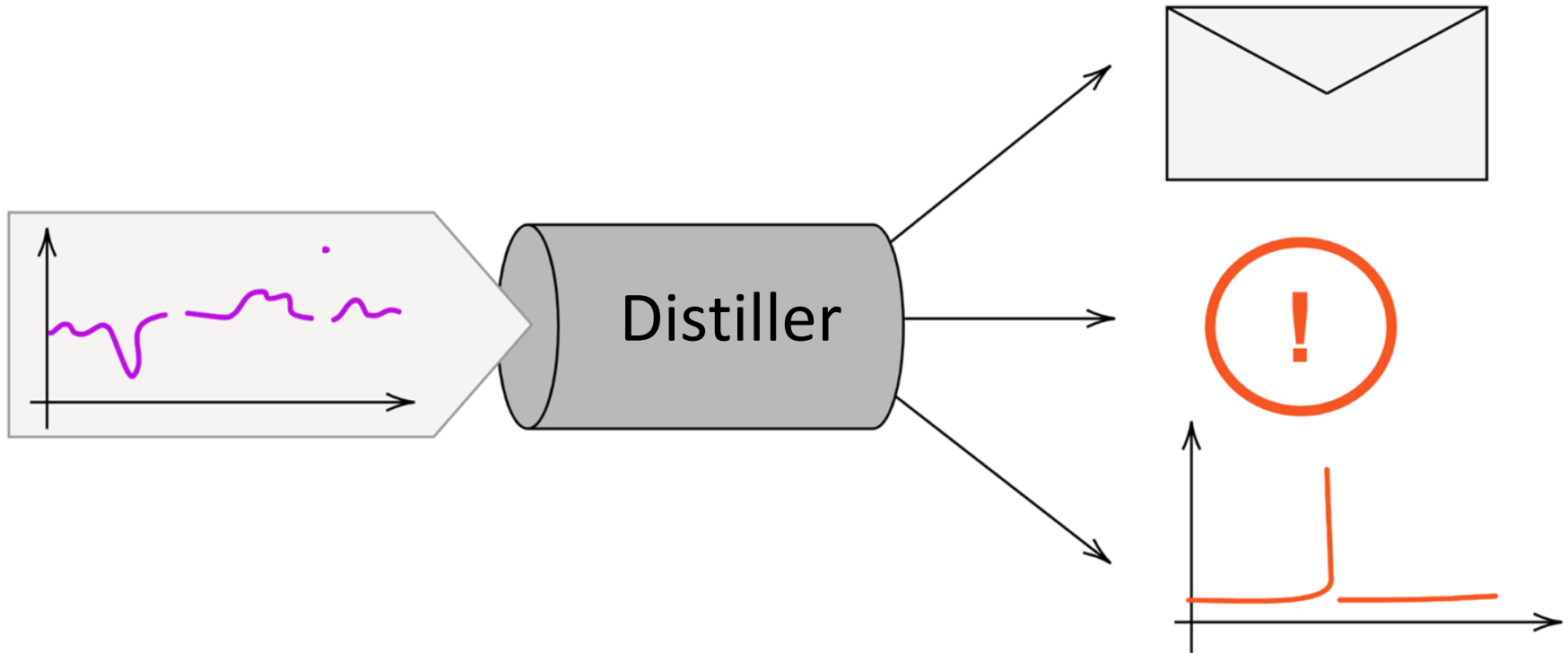


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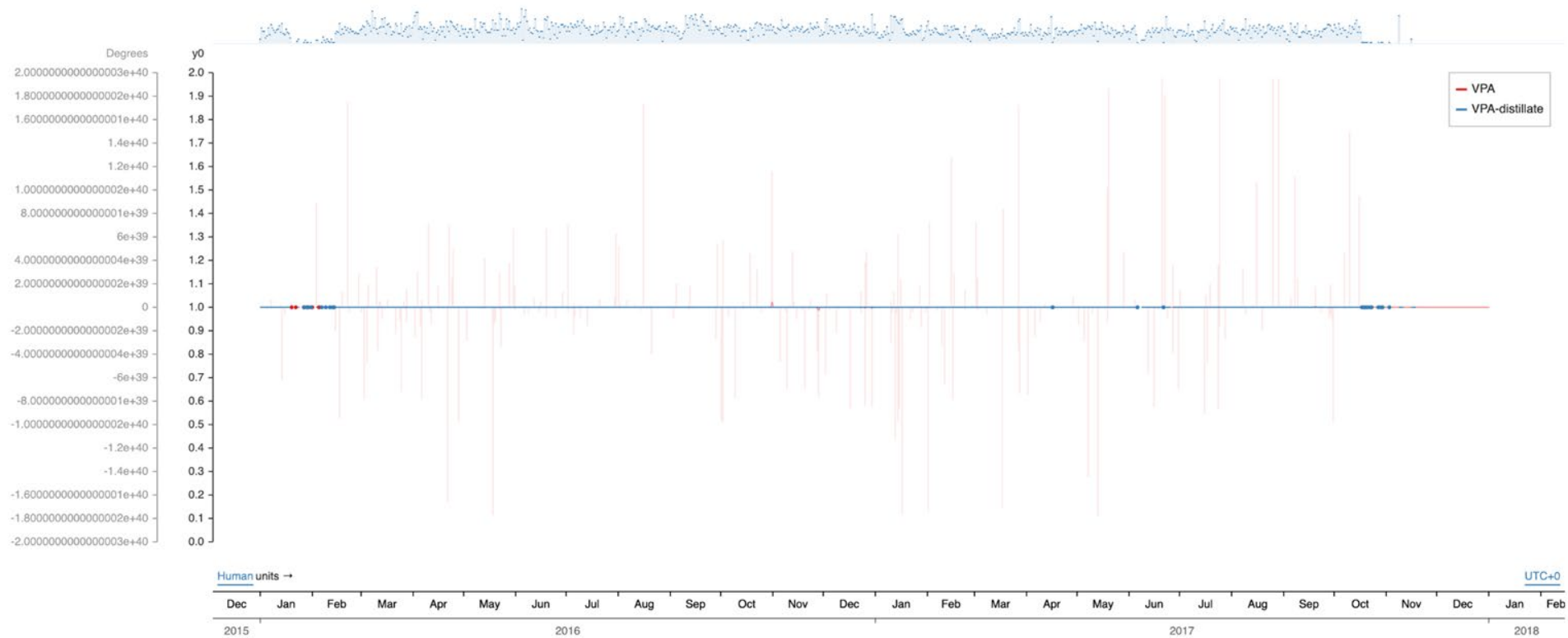
Data Quality Distillates - Understand & Flag DQ Issues



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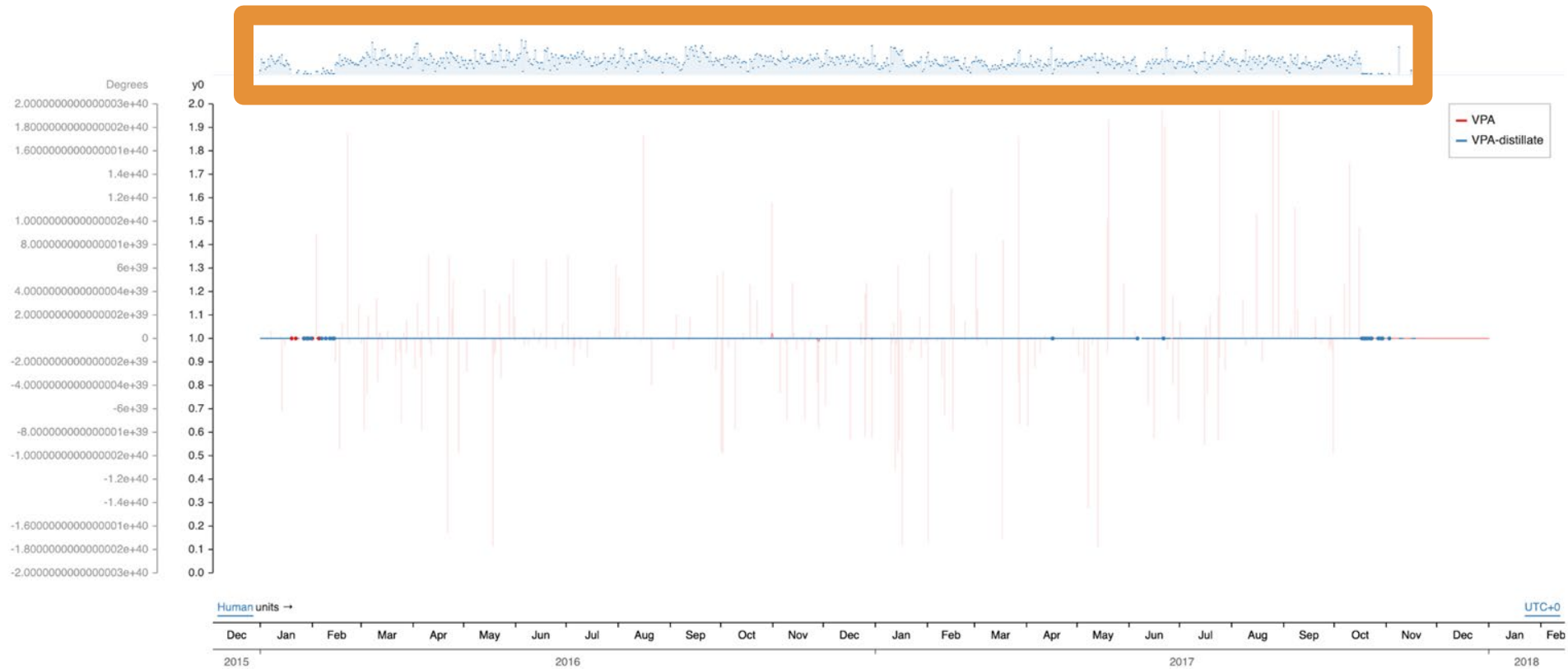
Data Quality Distillates - Understand & Flag DQ Issues



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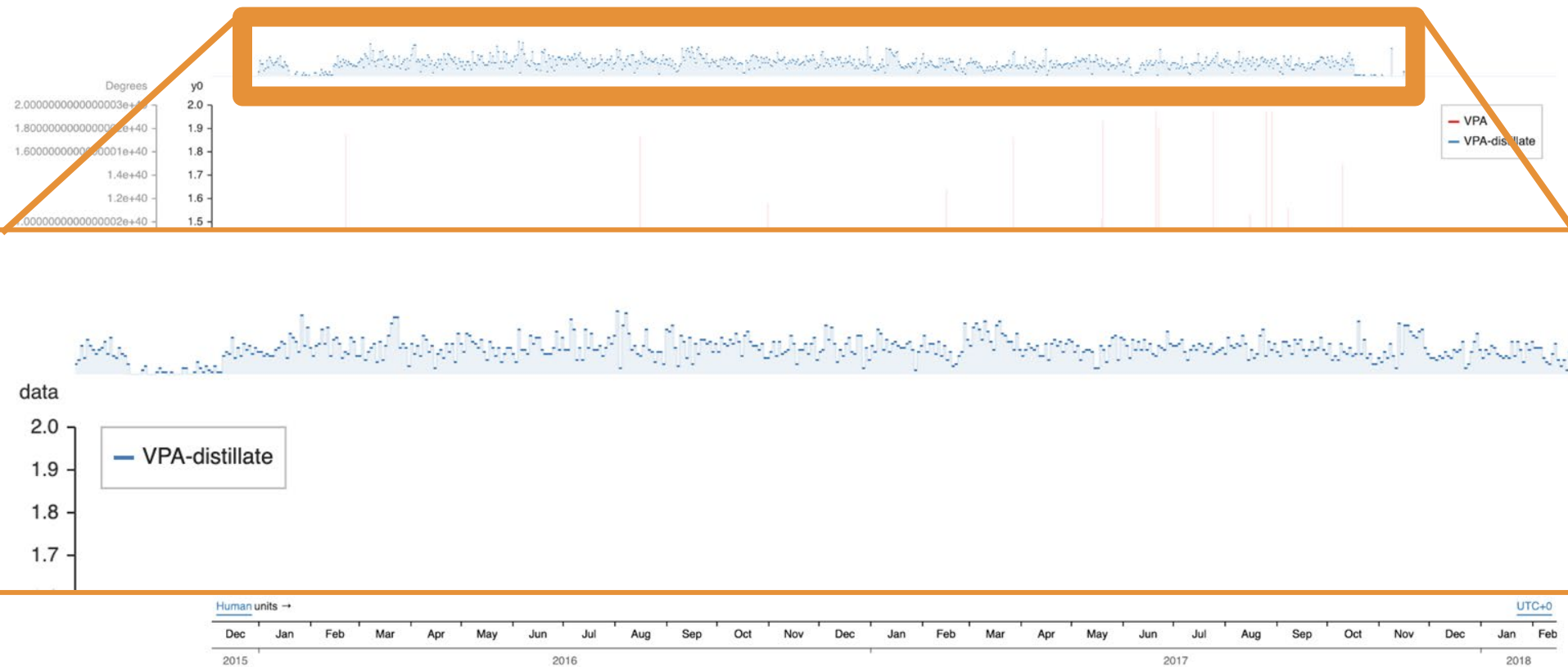
Data Quality Distillates - Understand & Flag DQ Issues



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Data Quality Distillates - Understand & Flag DQ Issues



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Augmenting Logs - Labelling App

```
In [1]: from labeling import *  
l = MyLabels(user='john')
```

You have been assigned batches 1 to 12. Each has 25 events

You are at the beginning of your labeling exercise. No previous saved work found

1. Did the naive algo separate the streams correctly?

```
In [2]: labels_q1 = annotate(**l.get_kwargs_q1())
```

Current PlotId: 0

| | | | | |
|------|------|--------|------------|---------------------|
| yes | no | almost | mostly not | I dont see an event |
| prev | skip | | | |

See plot here: https://jupyter.collab.ptpg.dev/user/ramiro/view/notebooks_playground/labeling/plotid0.png

2. Select a time-range (x-axis) and a feature-range (y-axis) that captures the PMUs that recorded the event (if any):

```
In [3]: labels_q2 = annotate(**l.get_kwargs_q2())
```

Current PlotId: 0

| | | |
|--------|----------------------|------|
| x1 | <input type="text"/> | 0.00 |
| x2 | <input type="text"/> | 0.00 |
| y1 | <input type="text"/> | 0.00 |
| y2 | <input type="text"/> | 0.00 |
| submit | prev | skip |

0

3. Which feature (eg Voltage, Current, etc) do the x,y coordinates provided correspond to? (you can choose multiple features)

```
In [4]: labels_q3 = annotate(**l.get_kwargs_q3())
```

Current PlotId: 0

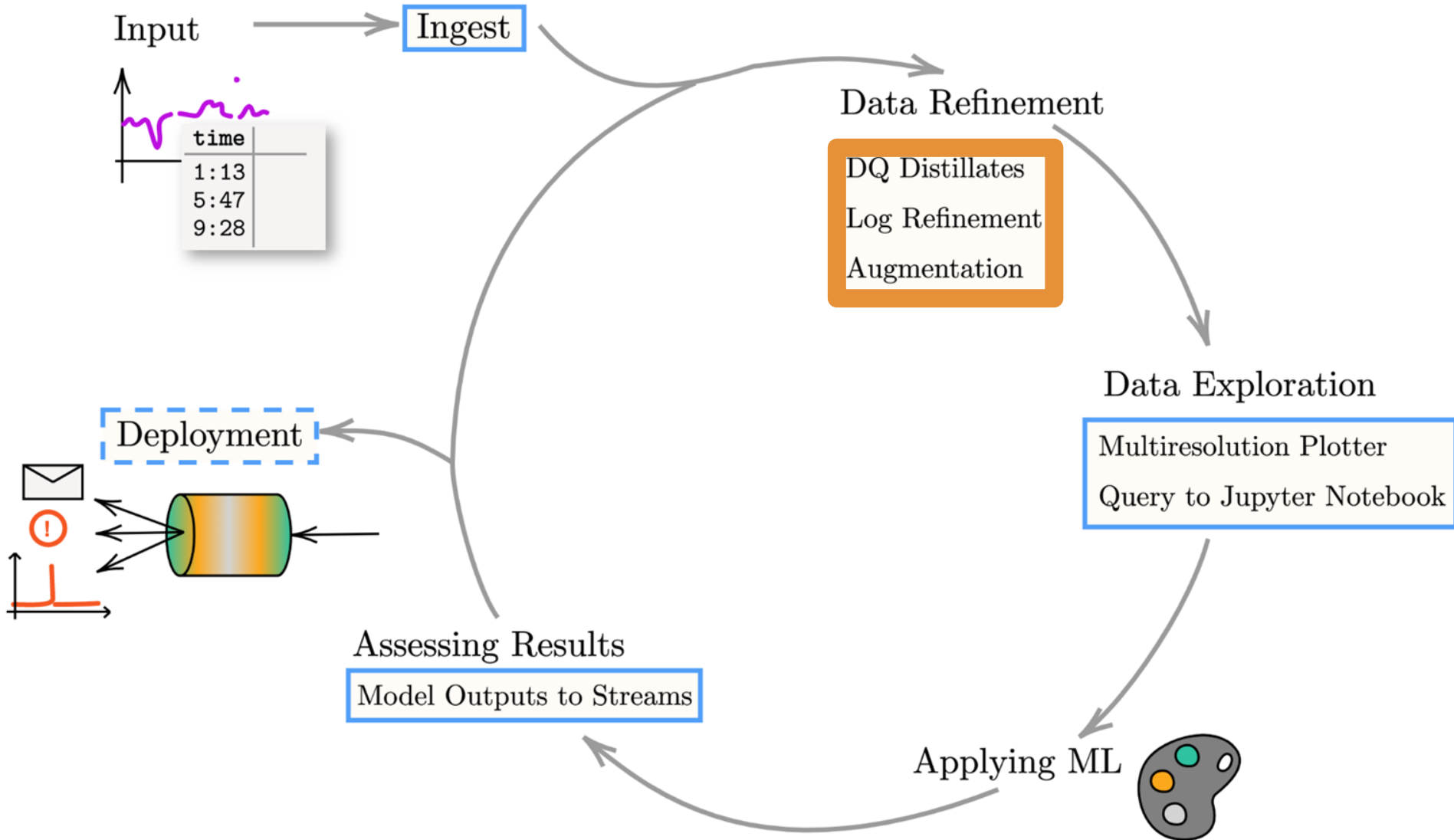
| | | | |
|------|-----|--------|------|
| VPM | IPM | submit | prev |
| skip | | | |



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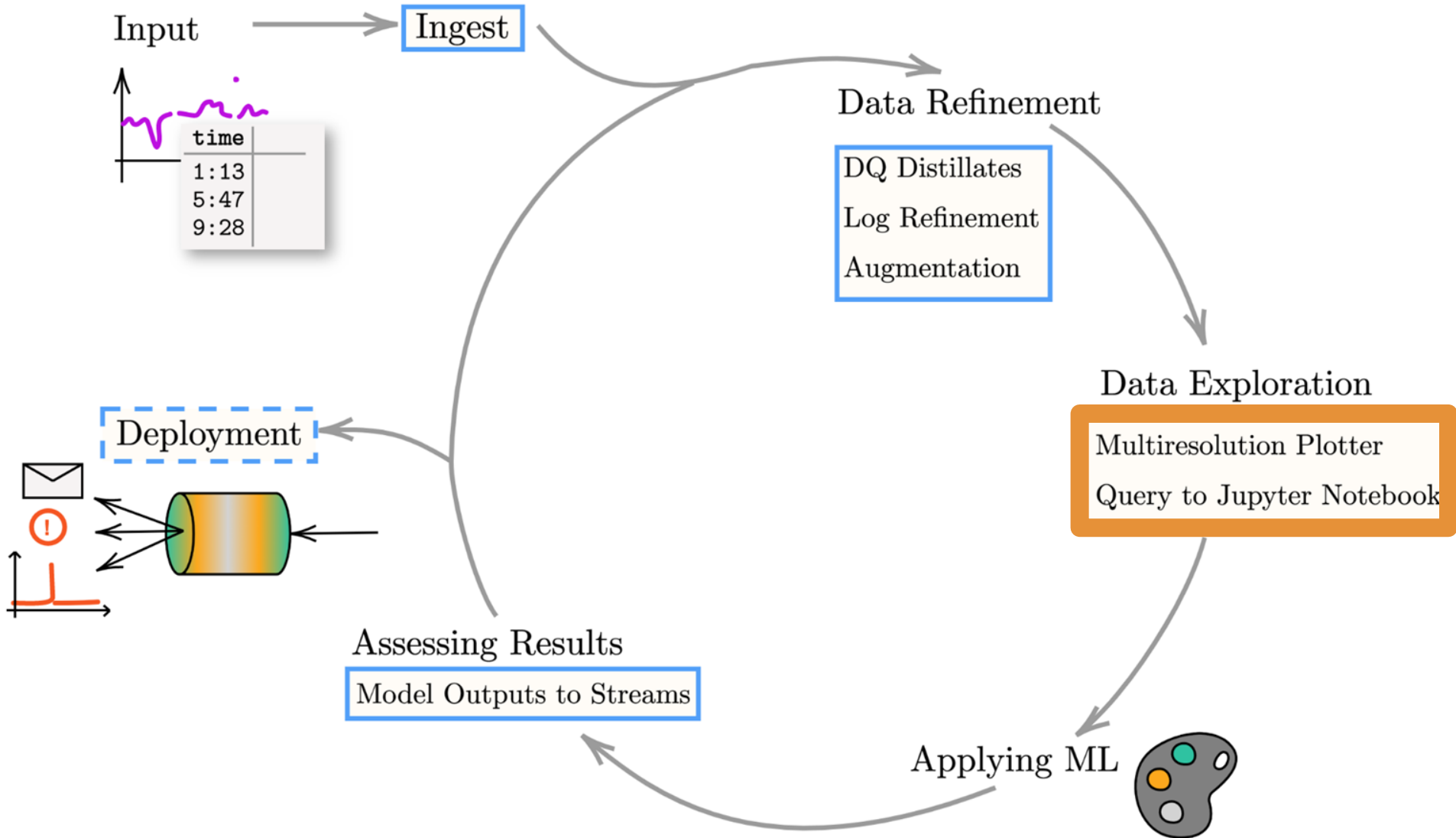
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Data Exploration

Multiresolution Plotter

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Stream Selection

Map

Stream Visualization

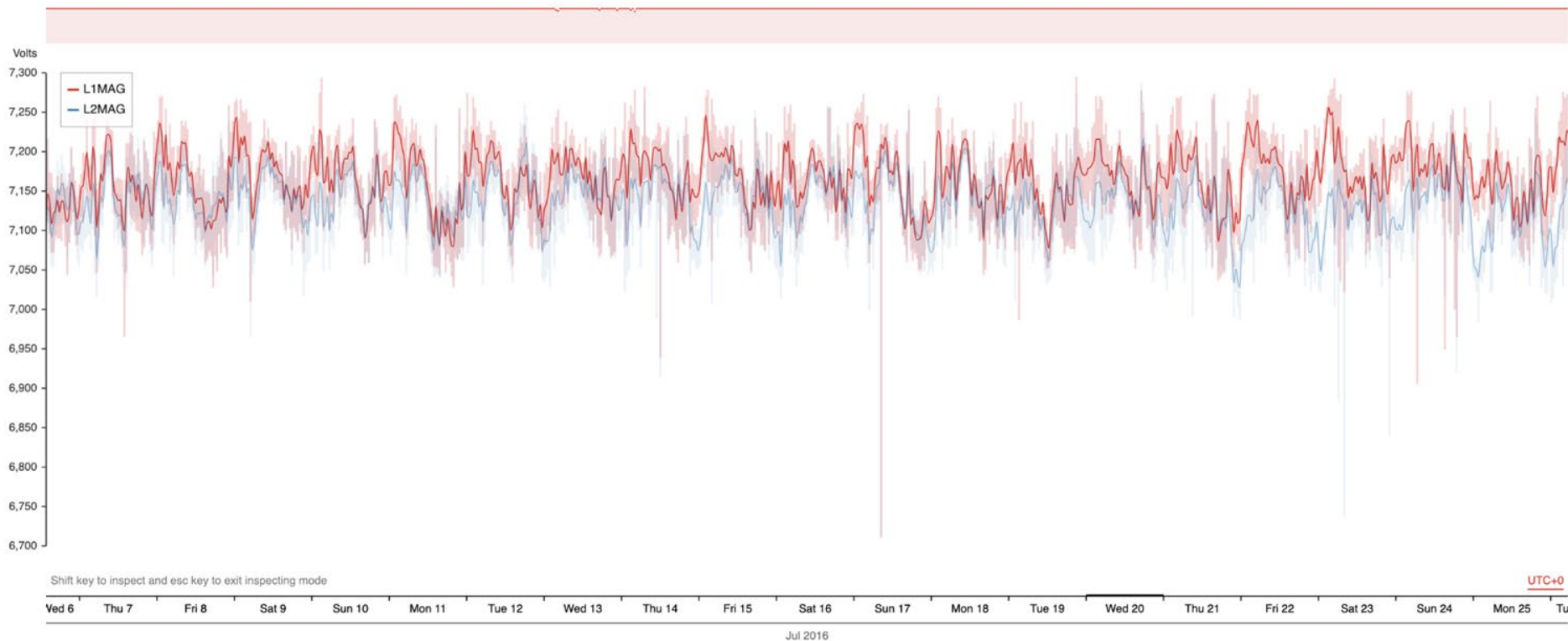


Plotter



Log in

Reset Zoom



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Data Exploration

Jupyter Notebooks

Power factor at PMU 4

```
In [142]: # Get streams
uuids = db.query("SELECT collection, name FROM streams WHERE collection like 'sunshine/PMU4'")
names = [row["collection"]+"/"+row["name"] for row in uuids]
streams = db.streams(*names)
print(names)

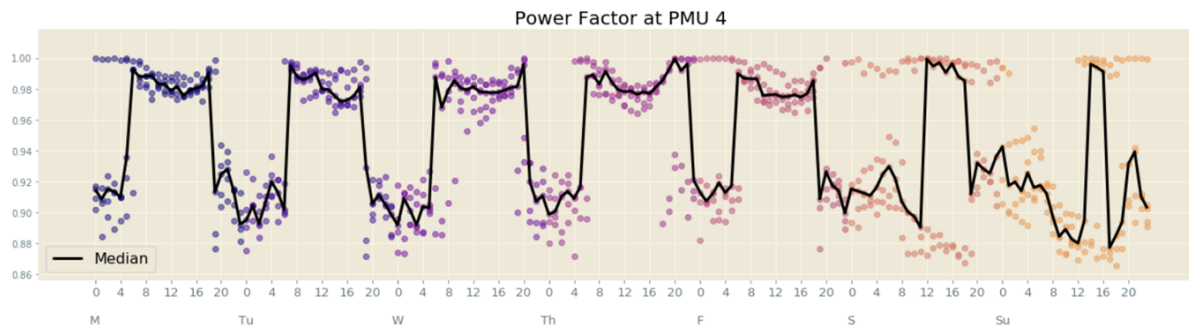
['sunshine/PMU4/C1MAG', 'sunshine/PMU4/L1MAG', 'sunshine/PMU4/C2ANG', 'sunshine/PMU4/C2MAG', 'sunshine/PMU4/L3MAG',
'sunshine/PMU4/L2MAG', 'sunshine/PMU4/C3MAG', 'sunshine/PMU4/L2ANG', 'sunshine/PMU4/C1ANG', 'sunshine/PMU4/L1ANG', 's
unshine/PMU4/L3ANG', 'sunshine/PMU4/C3ANG', 'sunshine/PMU4/LSTATE']
```

```
In [143]: vang_stream = streams[9]; iang_stream = streams[8];
#t0 = ns_to_datetime(vang_stream.earliest()[0].time) + datetime.timedelta(days=10);
# start on monday, july 27, 2015
t0 = datetime.datetime(2015, 7, 27) + datetime.timedelta(hours=7);
```

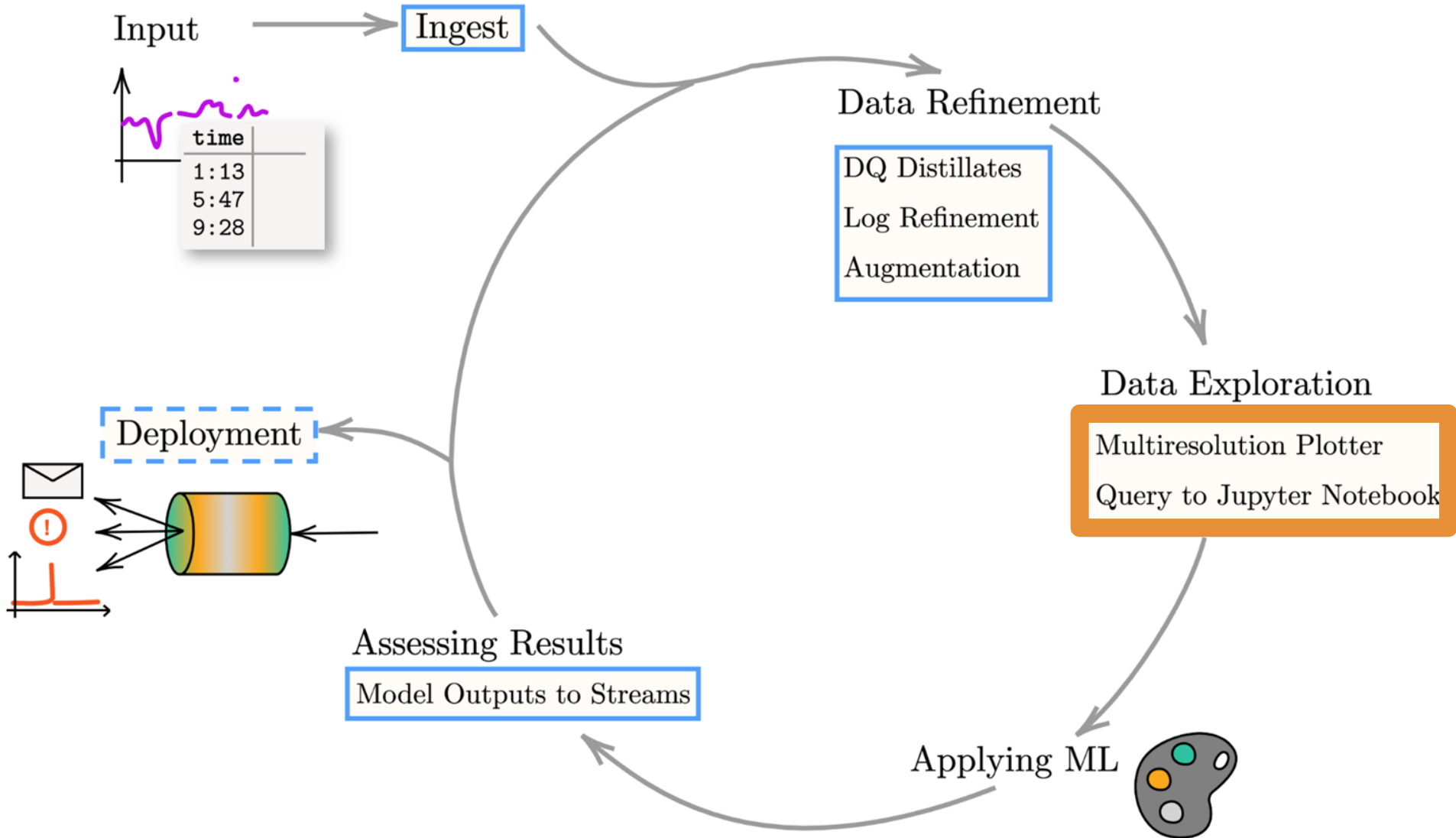
```
In [144]: pf_pmu4 = powerfactor_weeks(vang_stream = vang_stream, iang_stream = iang_stream, time = t0)
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

```
In [145]: pfmed_pmu4 = plot_hourly_pf(pf_pmu4);
plt.title('Power Factor at PMU 4', fontsize=20);
plt.tight_layout();
plt.savefig('pf_pmu4', dpi=200);
```



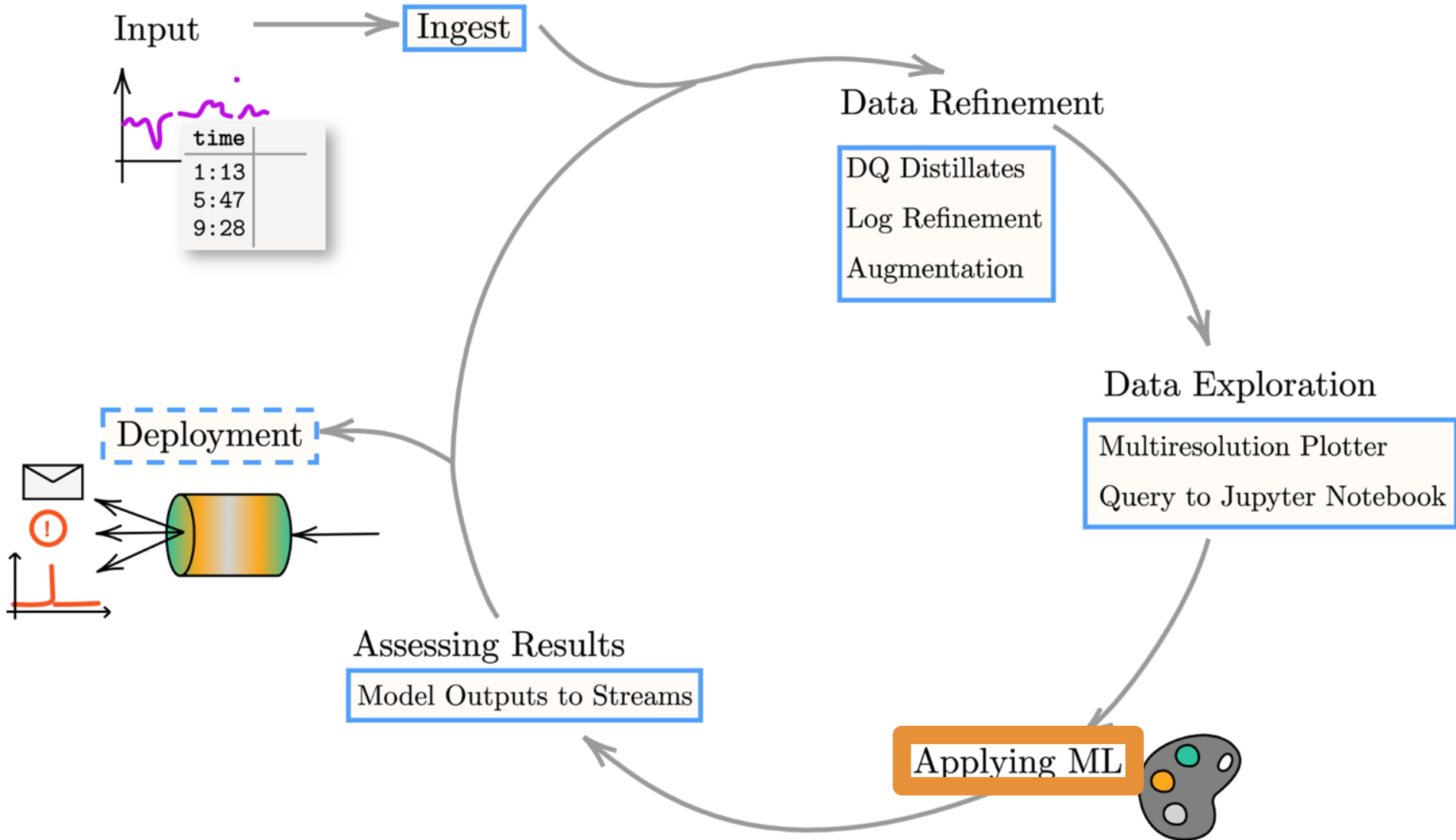
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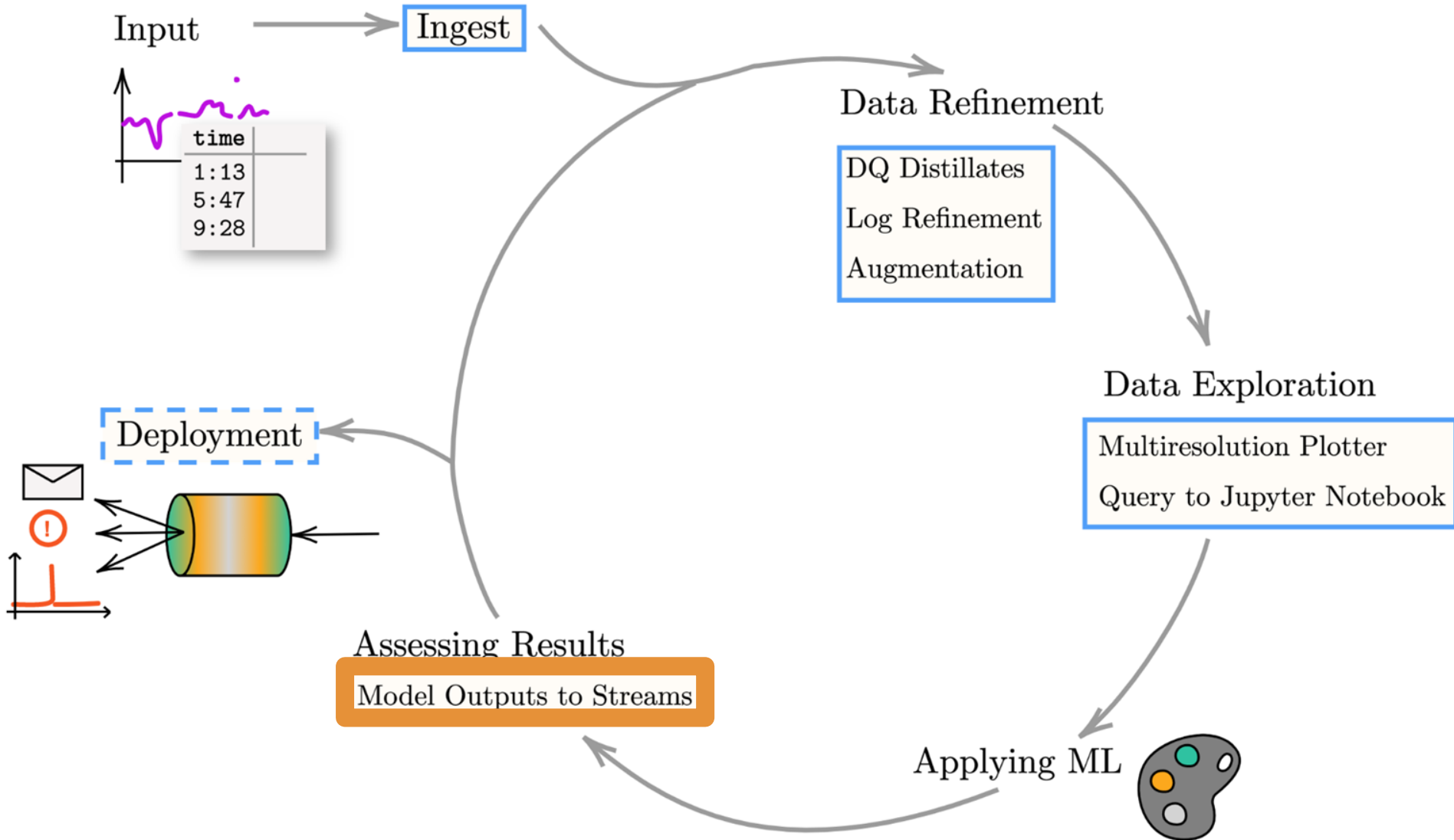
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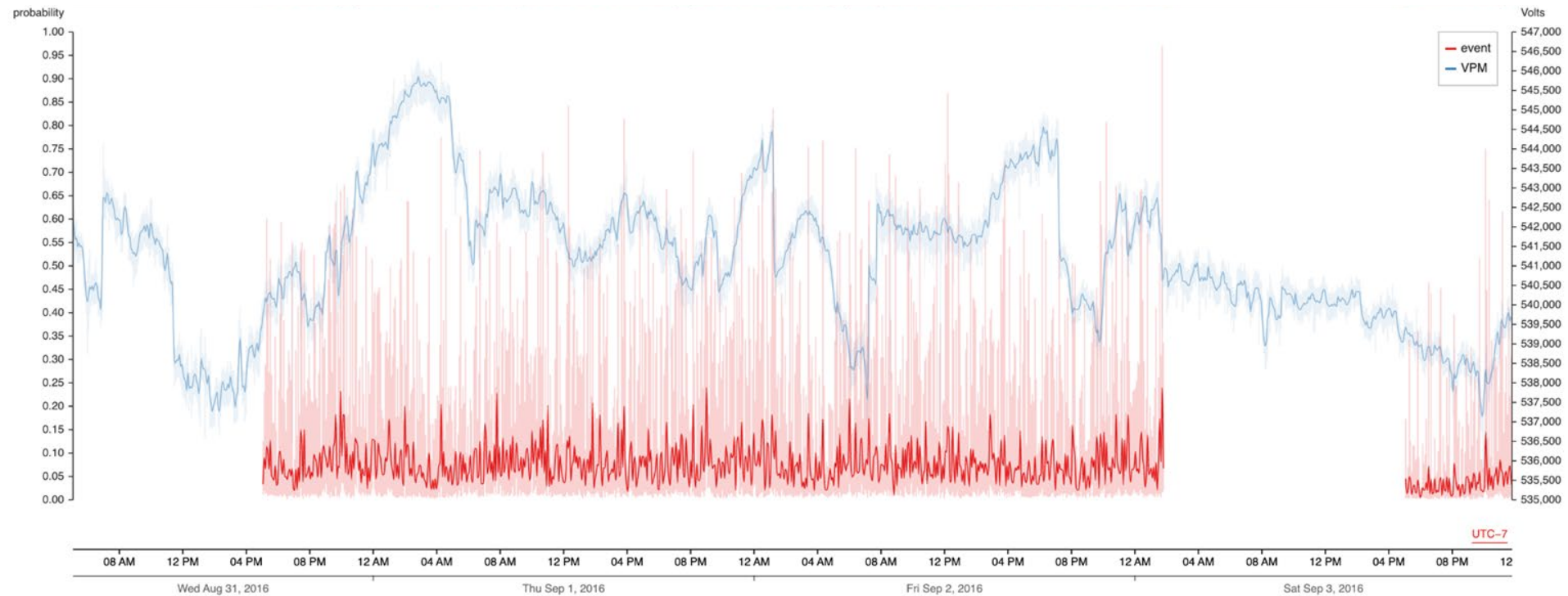


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Assessing Results

Model Outputs to Streams

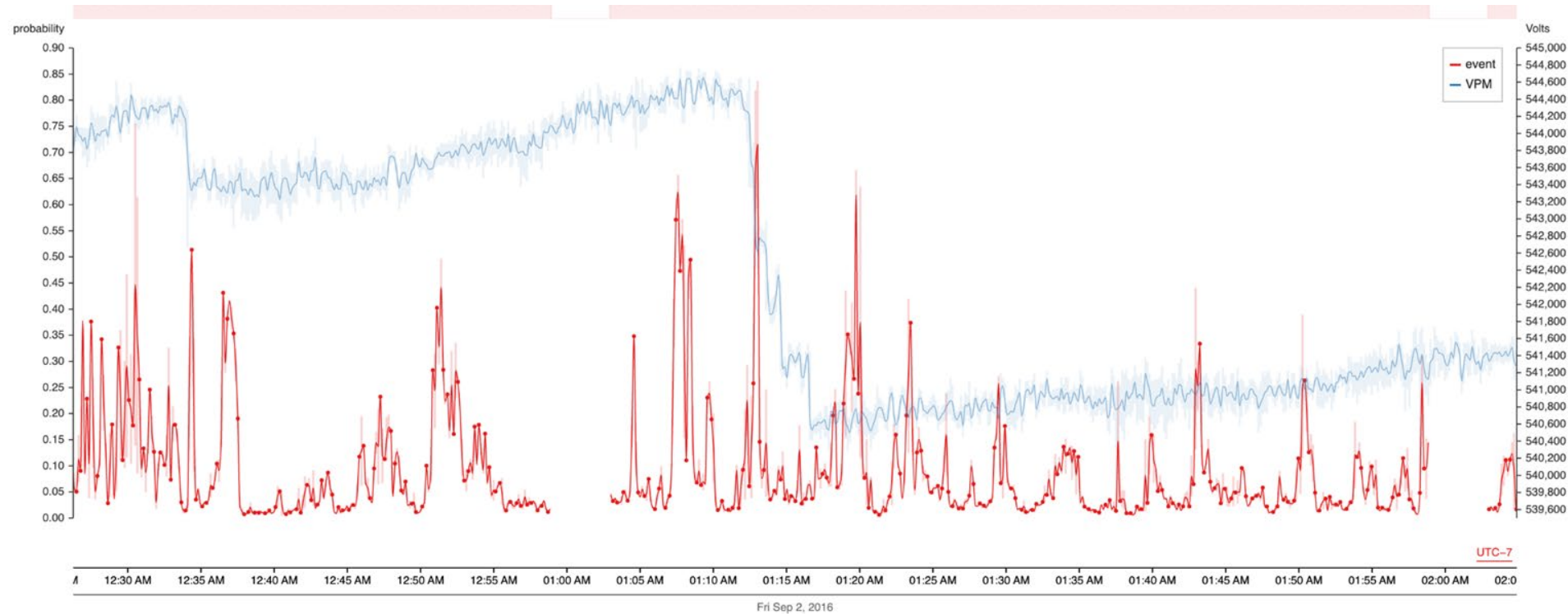


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Assessing Results

Model Outputs to Streams

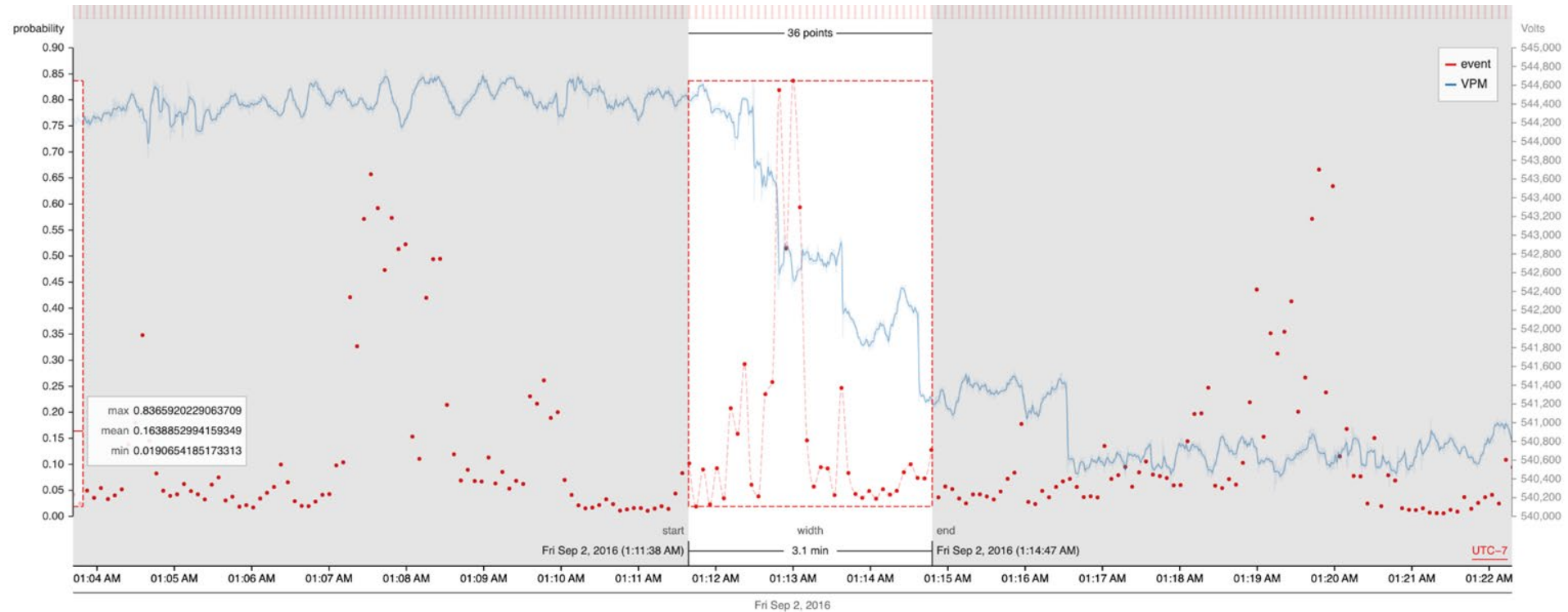


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Assessing Results

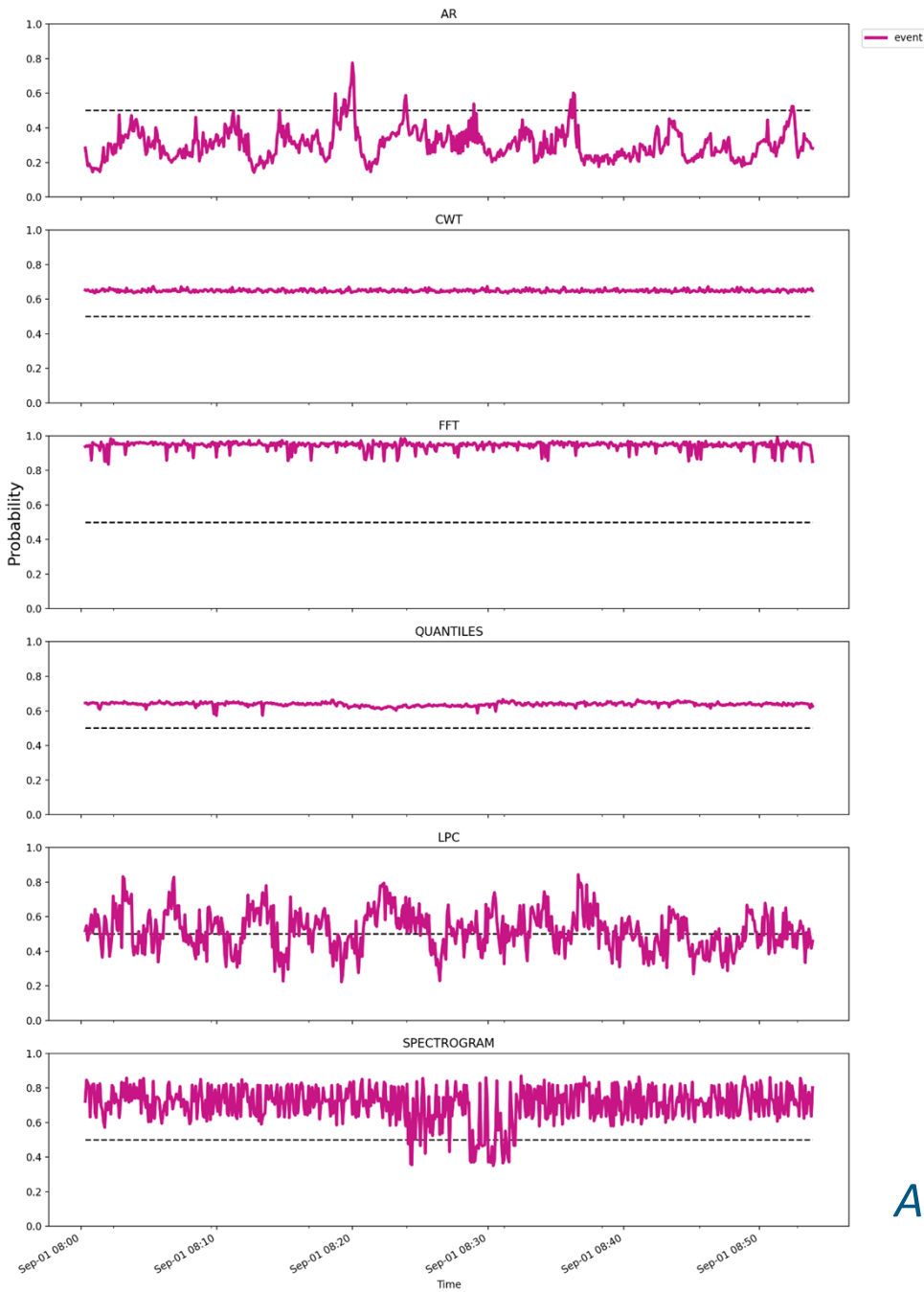
Model Outputs to Streams



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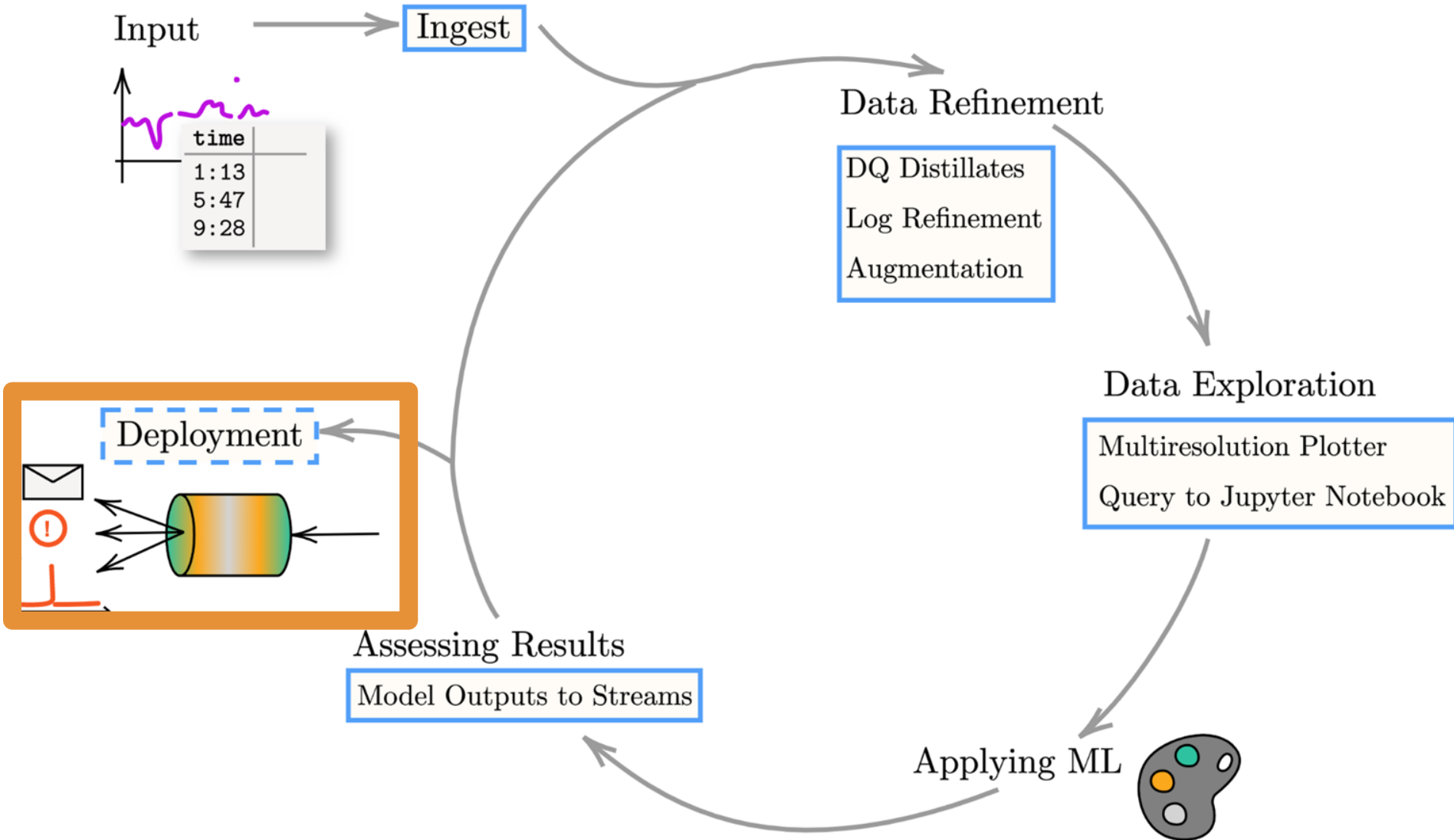


Assessing Results



A enormous need for results exploration

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Value of Work

Tools

- In 5 years: Operators & engineers collaborate with ever stronger ML models.
- Many use cases! Broadly useful tools that can be tuned & applied to various applications & datasets.

Data

- Sharing anonymized data is critical! This dataset makes the impossible, possible.
- Real-world data from multiple contexts enables generalizable, efficacious algorithms.

Readiness for Commercialization



Ready for use:

- Tools for most stages of the analysis & design cycle.
- Refinement is always possible, but may best be done on the job.

Work with *you* on application to specific use cases.



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Being Ready for ML & BD Analytics

Difficulties

- More domain expertise can help with feature selection.
- Need more standardized assessment.
- Labels have poor temporal specificity & no spatial information.
- What is normal? More work to distinguish significant from inconsequential.

Recommendations

- Prepare data for ML: More measurements, define & save standardized records.
 - Records on how problem was discovered (measurements, call, manual)
 - Which streams revealed an issue?

Lessons Learned and Next Steps

Dataset should be made open access for further work and *accessible*.

For example, in the NI4AI project: <https://ni4ai.org/>

Next steps

- Greater focus on algorithmic transparency and visualization.
- Enabling feedback for learning on the job.



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Extra Slides

Extra slides after this point.



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Diversity of Model Types

| Model Type | Description |
|-------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CatBoost | Model consisting of ensemble of weaker classifiers, usually decision trees. |
| Decision Tree | Non-parametric model consisting of layered, simple decision rules. |
| Extra Trees | Fits a number of randomized decision trees on various sub-samples of the dataset. Uses averaging to improve the predictive accuracy and control over-fitting. |
| Gaussian Naive Bayes | Fits Gaussian distribution to data using Bayesian methods. |
| K Neighbors | Non-parametric method classifies new sample based on k nearest training samples. |
| LGBM | Model consisting of ensemble of weaker classifiers, usually decision trees. |
| MLP | Multi-layer perceptron, a type of neural network. |
| MLP Deep | A deep multi-layer perceptron. |
| Random Forest | Fits an ensemble of decision trees, which vote to produce a single classification. |
| SGD with hinge | Fits a linear classifier using stochastic gradient descent. The optimized loss function is the hinge loss. |
| SGD with log | Above, but the optimized loss function is the log loss. |
| SGD with modified Huber | Above, but the optimized loss function is the modified Huber loss. |

Diversity of Features

| Feature Family | Feature Types | Number of Features |
|------------------------------------|----------------------------------------------|--------------------|
| Auto-regressive | Aggregated Autocorrelation | 186 |
| | AR Coefficient | 186 |
| | Aggregated Linear Trend | 186 |
| Quantiles | Quantiles | 207 |
| | Change Quantiles | 207 |
| | Coefficient of Variation | 207 |
| Continuous Wavelet Transform (CWT) | CWT using the Ricker aka Mexican Hat Wavelet | 180 |
| Fast Fourier Transform (FFT) | FFT | 1200 |
| Spectrogram | Spectrogram | 405 |

Publications



————— INSERT ORG LOGO (Optional) —————

