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Machine Learning on Streams

Ram Sriharsha

Sr Director, Head of Machine Learning | Splunk

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Agenda

1) A sample problem and its real-world use case

2) Solving for scale and operational Simplicity

3) Where are we going from here?

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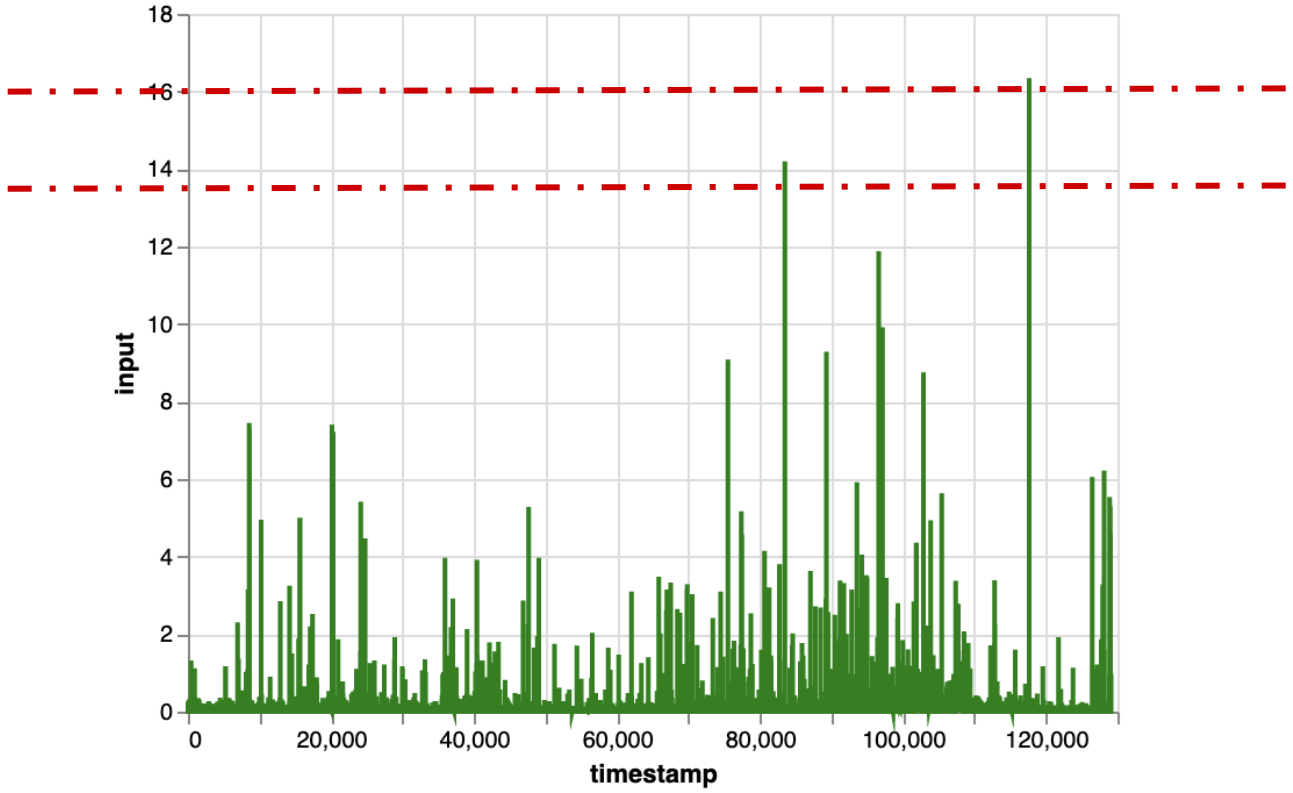
A Sample Problem

We have a time series. We would like to detect outliers in this time series
Naive approach = static thresholds.



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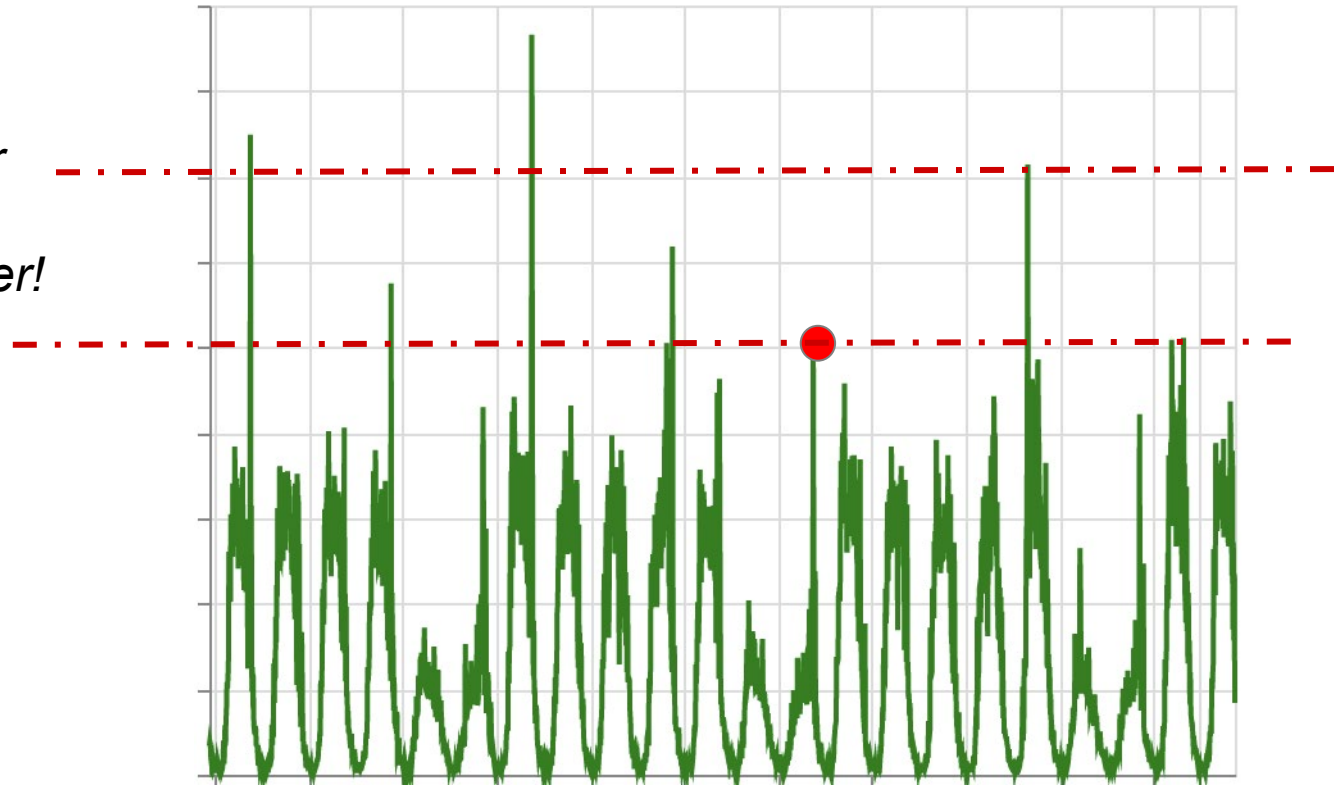
What if the Metric Has Seasonality?

Static Threshold either has too much noise or doesn't catch the outlier!



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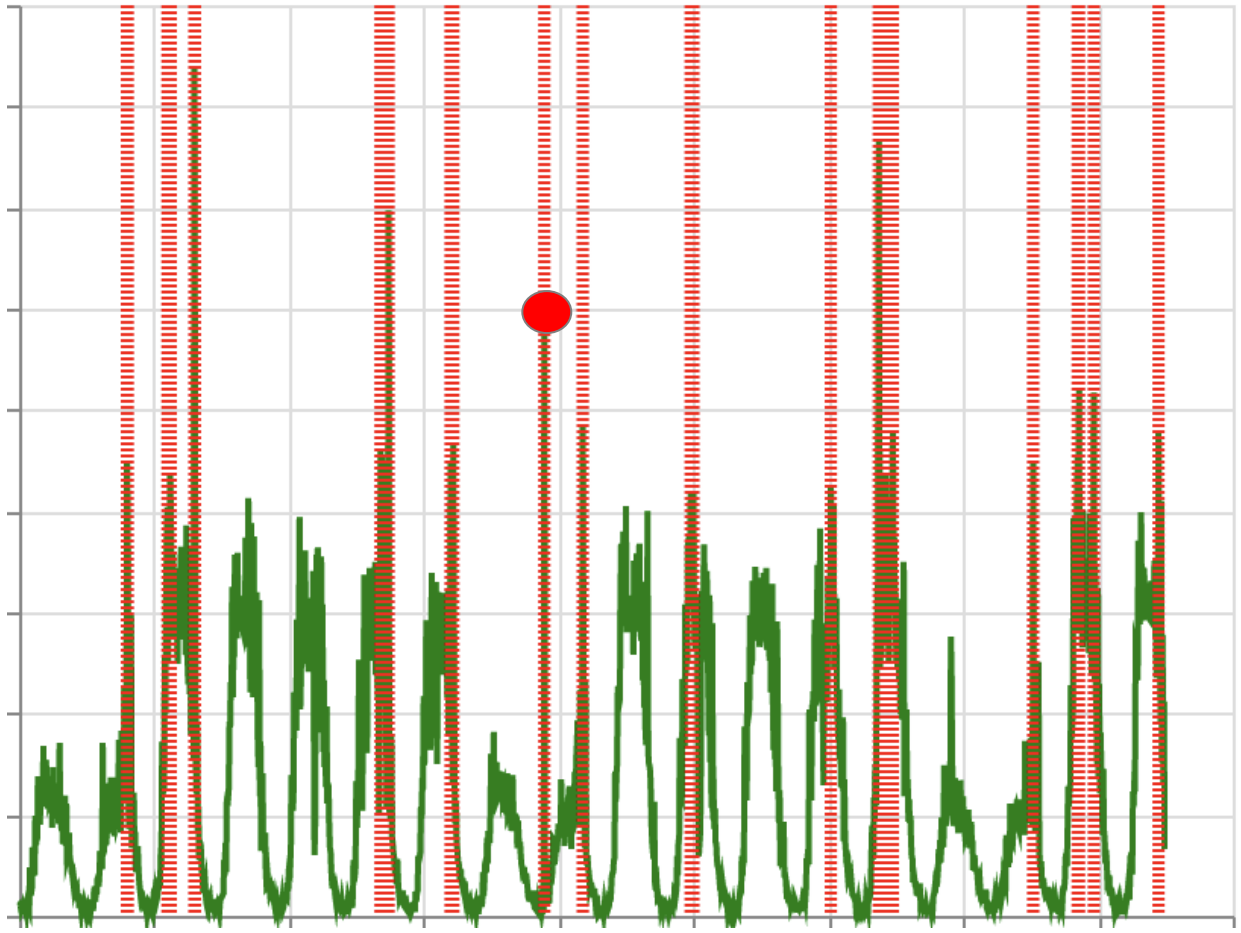
What if the Metric Has Seasonality?

Even adaptive threshold doesn't fare much better!



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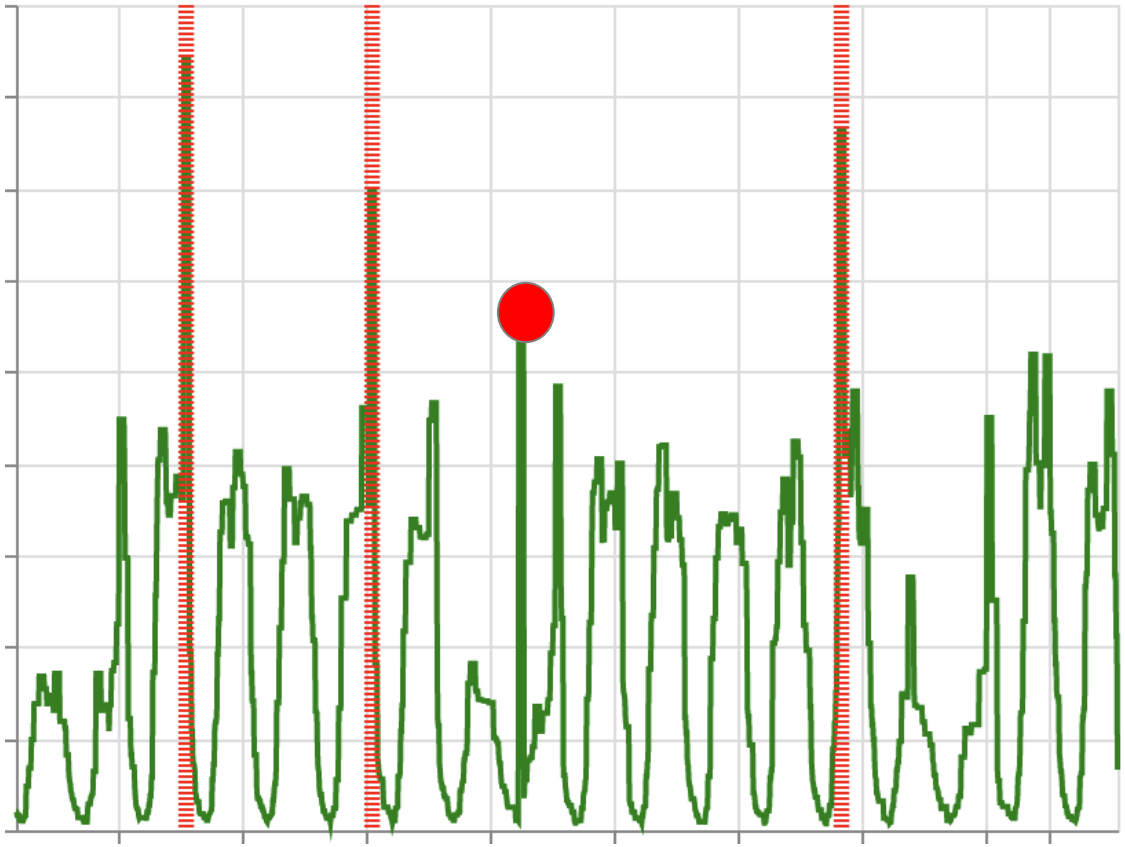
Maybe Preprocess?

Compute 95th percentile over last two hours and apply adaptive thresholding -> YMMV



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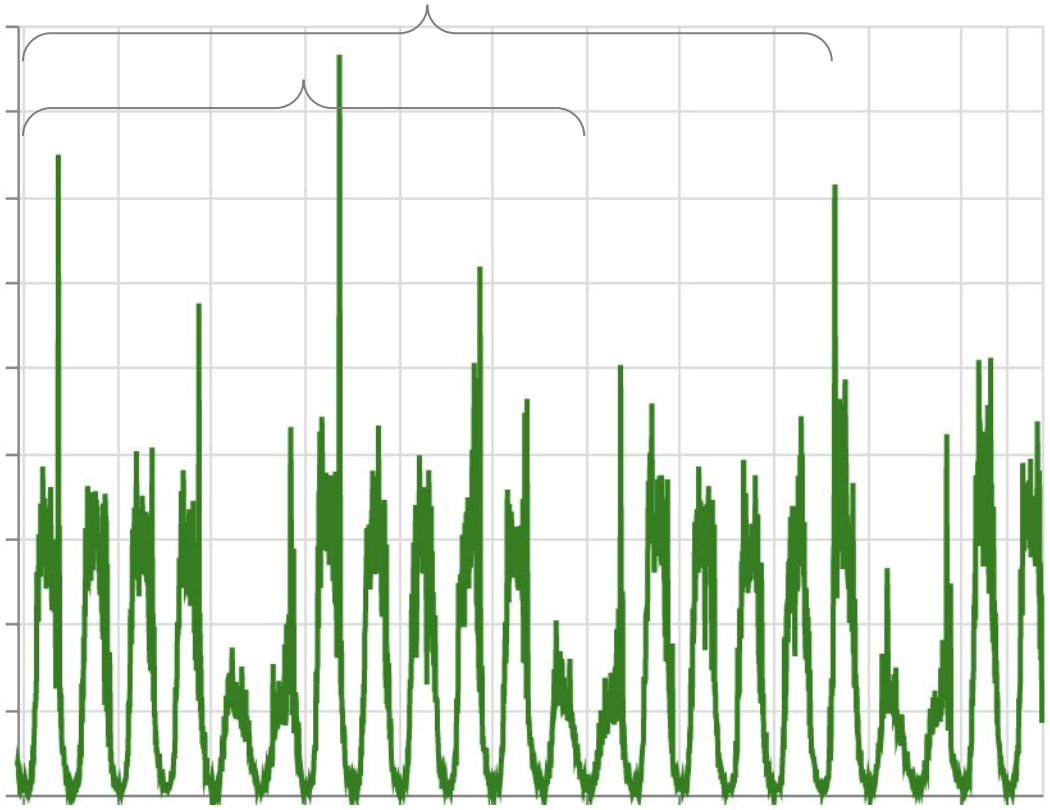
A Better Solution

Learn a model of time series based on past,
use that to predict outliers in the present



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Many Ways to Do This!

ARMA/ ARIMA/ SARIMAX

- Decompose time series into Autoregressive Moving Avg
- Use Seasonal differencing and de-trending to make the signal stationary

STL

- Direct decomposition of time series into seasonal, trend and residual
- Loess smoothing

Probability Density Function

- Fit a kernel density function for a multiple of seasonality
- Tune for a small % of errors
- Use fitted function to predict outliers in new data

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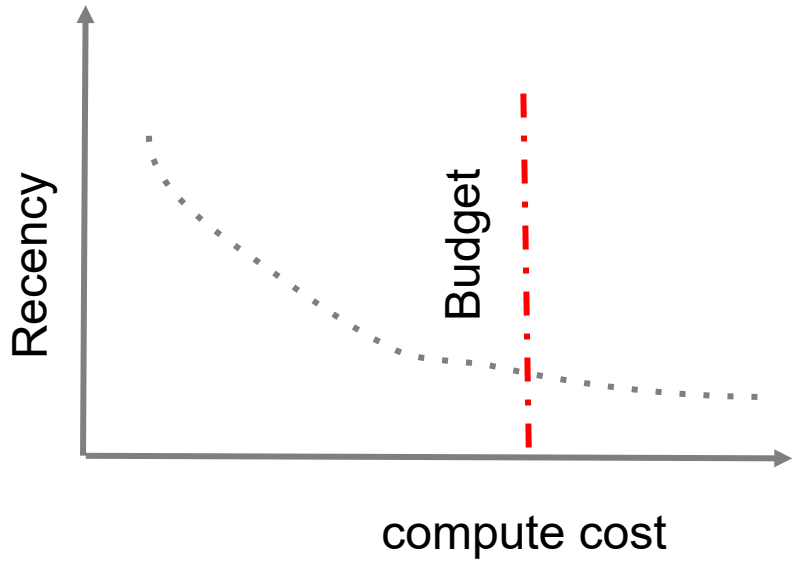
They All Have Problems!

All these approaches are batch algorithms

- Retraining on each data point = prohibitive
- Typically trained on last X days/ weeks and recency of a day or week
- Frequent retraining >> more complex models



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Doing This at Scale!

We collect multiple petabytes of logs from thousands of applications real time daily. We metricize these logs which results up to a million metrics. We want to monitor these metrics for outliers

How do we even threshold a million metrics?

- Logistically impossible to even set up!

Do these metrics contain any seasonality? if so, how do we handle it?

- Cannot possibly individually analyze each metric and model separately
- Current batch approaches are trained on a few weeks worth of data and run as weekly jobs => stale data!!

How do we deploy and monitor these systems?

- Even if we build O(100k) models, how do we deploy them, score on stream and monitor?

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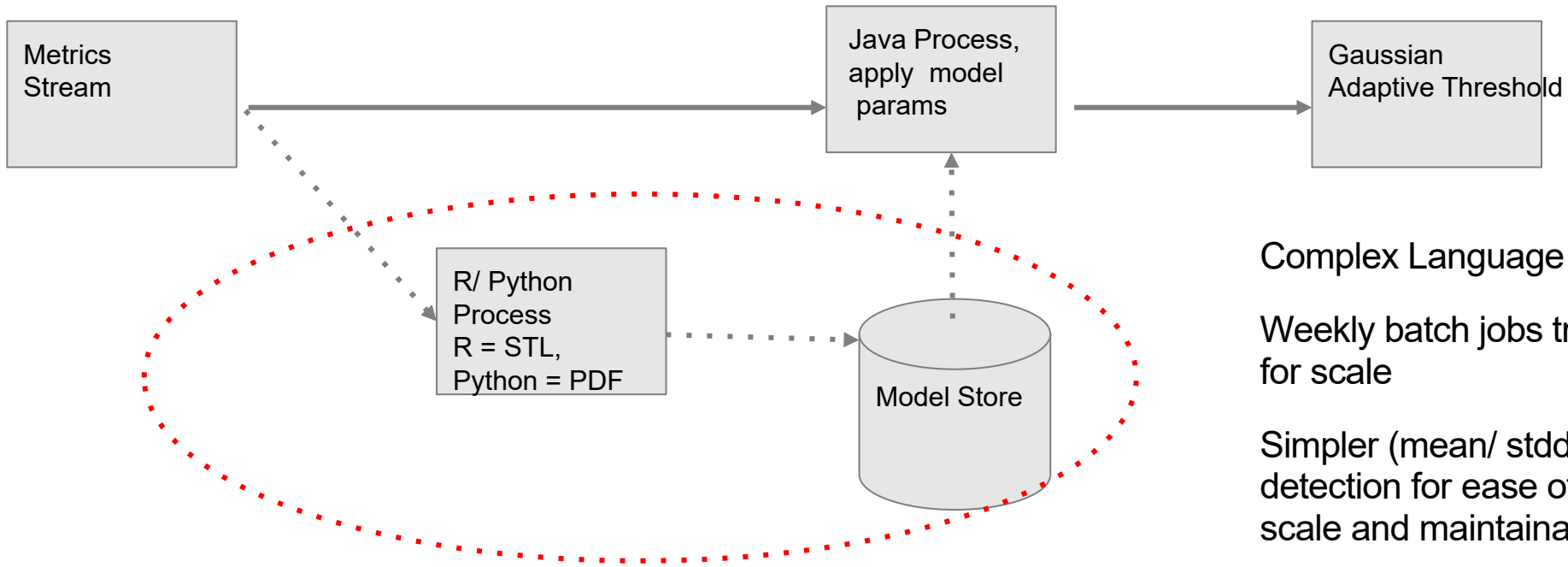
How is This Done Today?



Complex Language Bindings

Weekly batch jobs trade off recency for scale

Simpler (mean/ stddev) outlier detection for ease of development, scale and maintainability

Customers need to manage state, scalability, operationalization etc.

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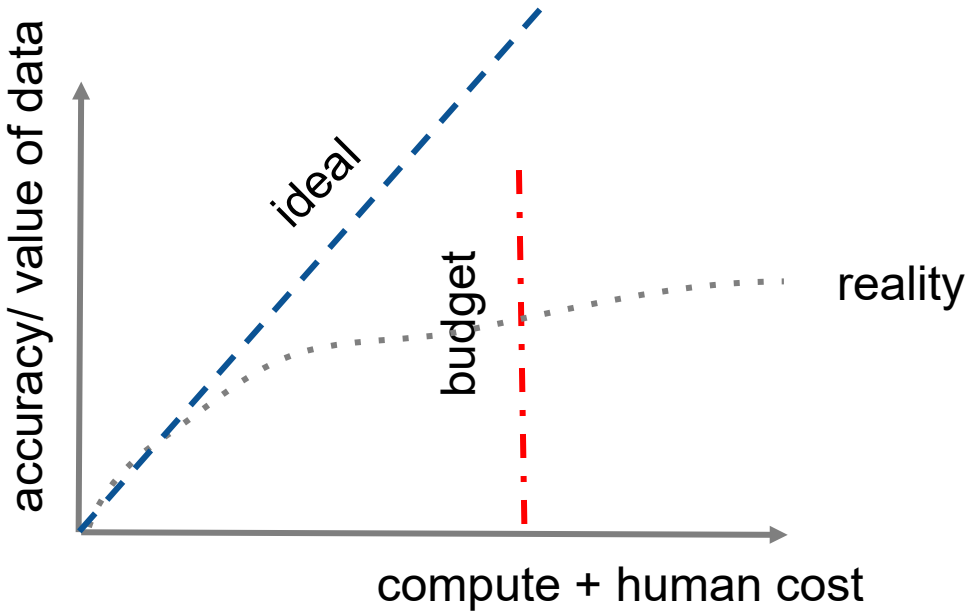
These Challenges Generalize to Many ML Use Cases!

Traditional ML = batch

- Retraining on each data point = prohibitive
- Modeling / Feature Engineering cost does not scale as number of models grow!

Frequent retraining >> more complex models



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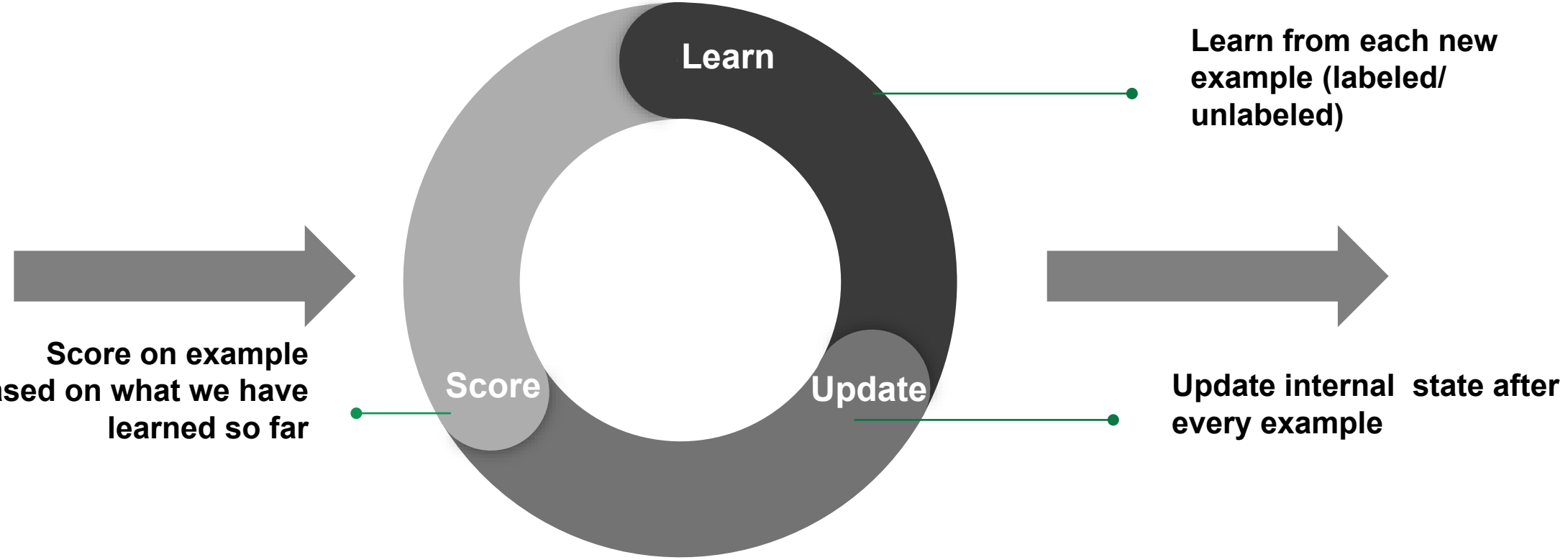
How to Get Closer to Ideal Tradeoff Curve?



We call them Unbounded learning systems!

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How Do We Solve the Toy Problem at Scale?


```
| from read_csv("s3://conf2020/errors.csv")
| eval body=_time
| extract_timestamp field="time" rules=[iso8601_timestamp()]
| stl value="input" seasonality=80
| eval key=concat([host, application)
| stats perc(residual, 0.95) as perc95 by key, span(time, 2h, 15min)
| eval timestamp=window_end
| adaptive_threshold value="perc95" entity="key";
```

- No Complex Language Bindings, simply use SPL!
- Models are always recent!
- More sophisticated adaptive thresholding including skewness adjustment possible
- We manage state, scalability, ops

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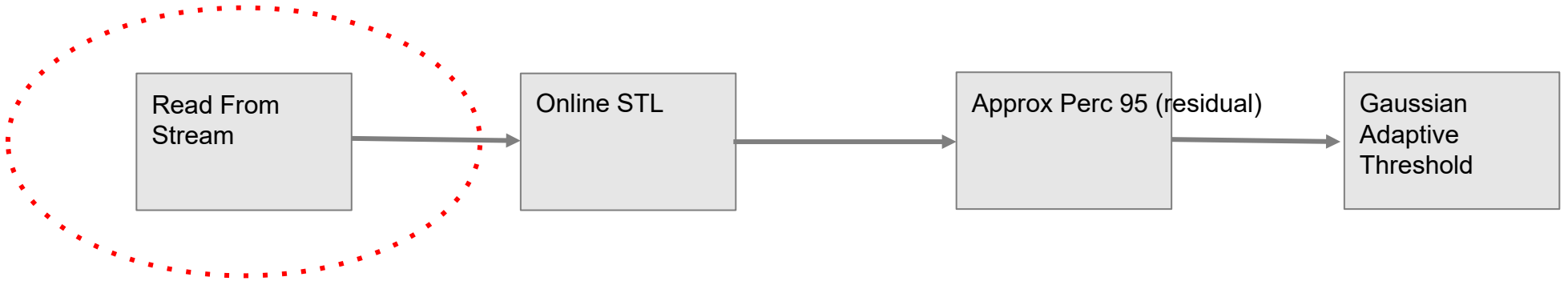
How Do You Deploy This in Production?




```
| from read_pulsar(topic=...)
| eval body=_time
| extract_timestamp field="time" rules=[iso8601_timestamp()]
| stl value="input" seasonality=80
| eval key=concat([host, application)
| stats perc(residual, 0.95) as perc95 by key, span(time, 2h, 15min)
| eval timestamp=window_end
| adaptive_threshold value="perc95" entity="key";
```

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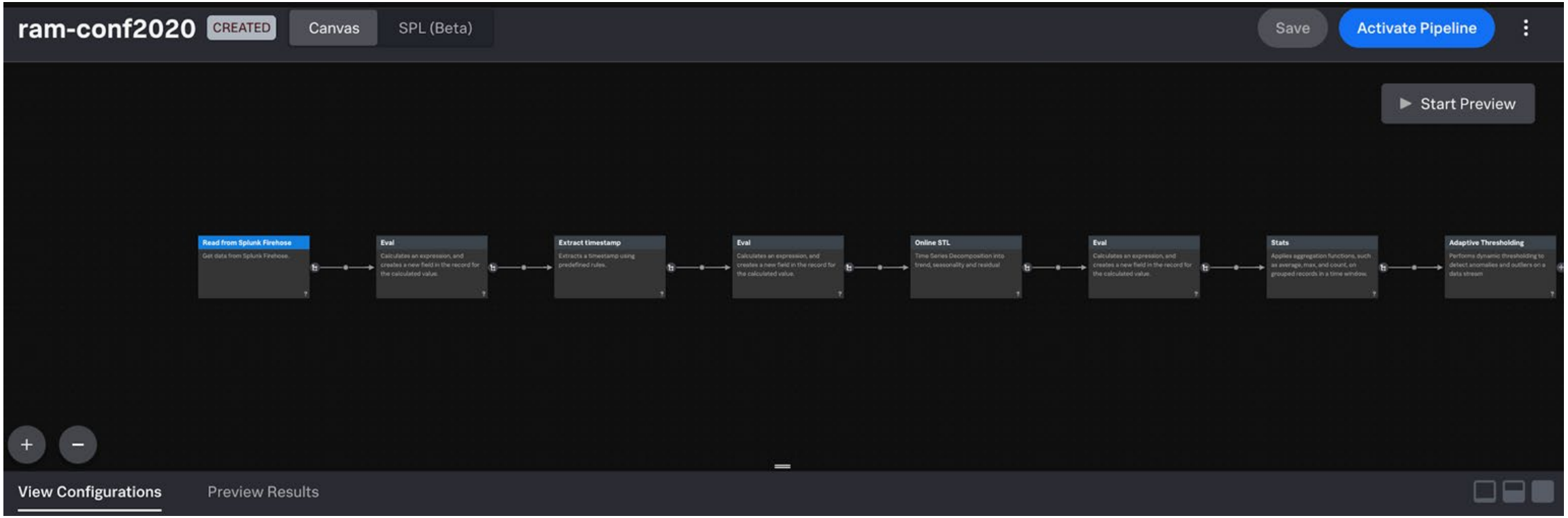
How Do You Deploy This in Production?



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Scale

40k

records per sec per core

50ms

max latency of ML pipeline outside of stats, ...

1mm

cardinality

100x

throughput compared to batch pipelines for same accuracy

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Other Algorithms Today

Outlier Detection

Adaptive Thresholding, Sequential Outlier Detection, Conditional Anomaly Detection

Time Series

Driift Detection, Online STL

Statistics/ ML

Online Clustering, Approx Perc, Distinct Count, Frequent Items

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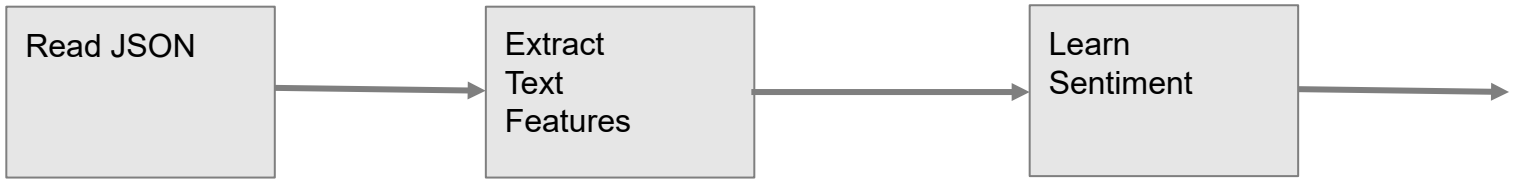
Another Example




```
| from read_json("s3://conf2020/reviews.json")
| eval  input=concat([reviewText," ",summary]),
    key=productCategory,
    label=if(overall >= 3.0, 1.0, -1.0)
| select input, label, key, reviewerID
| analyze_sentiment value="input";
```

- Sentiment Analysis learns from labeled examples
- Applies learning to unlabeled/ new examples
- Handles feature engineering as well as learning (eg. tokenization, word embedding and online learning)

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Design for Scale

Throw your data at the streaming algorithm and it will start to learn

- No pre-configuration needed, i.E self tuning
- Adapts to data
- Learns the distributions

Converges quickly

- Learning stabilizes soon

Unbounded in cardinality of models

- Learn as many models as you want , computational cost ~ linear in cardinality

Unbounded in data volume

Recency baked in - models are continually learning!

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Design Not Just For Scale

Drag and Drop streaming-ml pipelines

- Zero code experience
- One “click” deploy entire ML pipelines

SPL interoperability

- Use ML constructs within SPL to explore data, build pipelines

No downtime ML

- Upgrades to our algorithms do not require pipeline downtime
- No pesky version incompatibilities!

Scale, state and fault tolerance handled by us

- Do not have to re-engineer ML pipelines for production

Observability and Explain-ability of models built in

- Model metrics are available for the pipeline builder
- Explain-ability for various machine learning tasks to help triaging predictions

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Where are We Going With This?

Solve the problem of machine learning

- Learning in humans is constant and continuous. Why not in machines?

Make ML a seamless part of your pipeline

- just drop our ML in and let us do the hard work for you

Free you to focus on domain expertise and adding domain knowledge/ rules/ labels where needed

- leverage our labeling framework to provide weak labels as needed

Obtain insights while the data is in motion

Thank You

Please provide feedback via the

SESSION SURVEY