SCHOOL OF DATA ANALYSIS

NATIONAL RESEARCH UNIVERSITY

Yandex Data Popularity at LHCb and Beyond

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Operational Intelligence Meeting

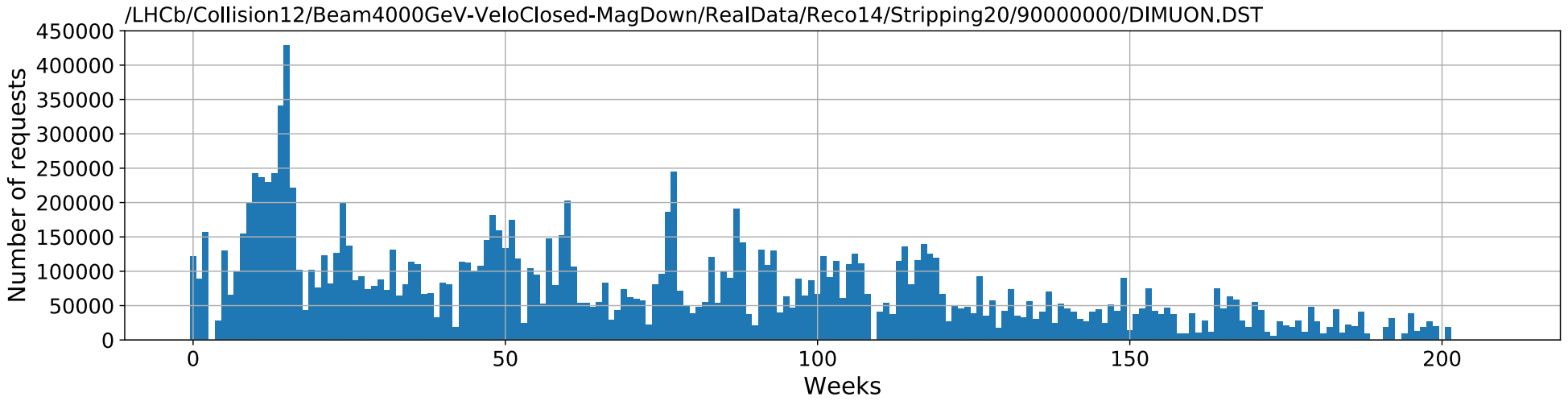
10 June, 2019

Outline

- Data Popularity at LHCb Recap
- Production Monitoring Automation Ideas

Data Popularity Prediction

Problem Formulation



- Predict LHCb datasets usage (popularity) in future based on their usage in the past
- Estimate optimal number of replicas on disks
- Estimate when a dataset can be transferred to a cold storage (tapes)

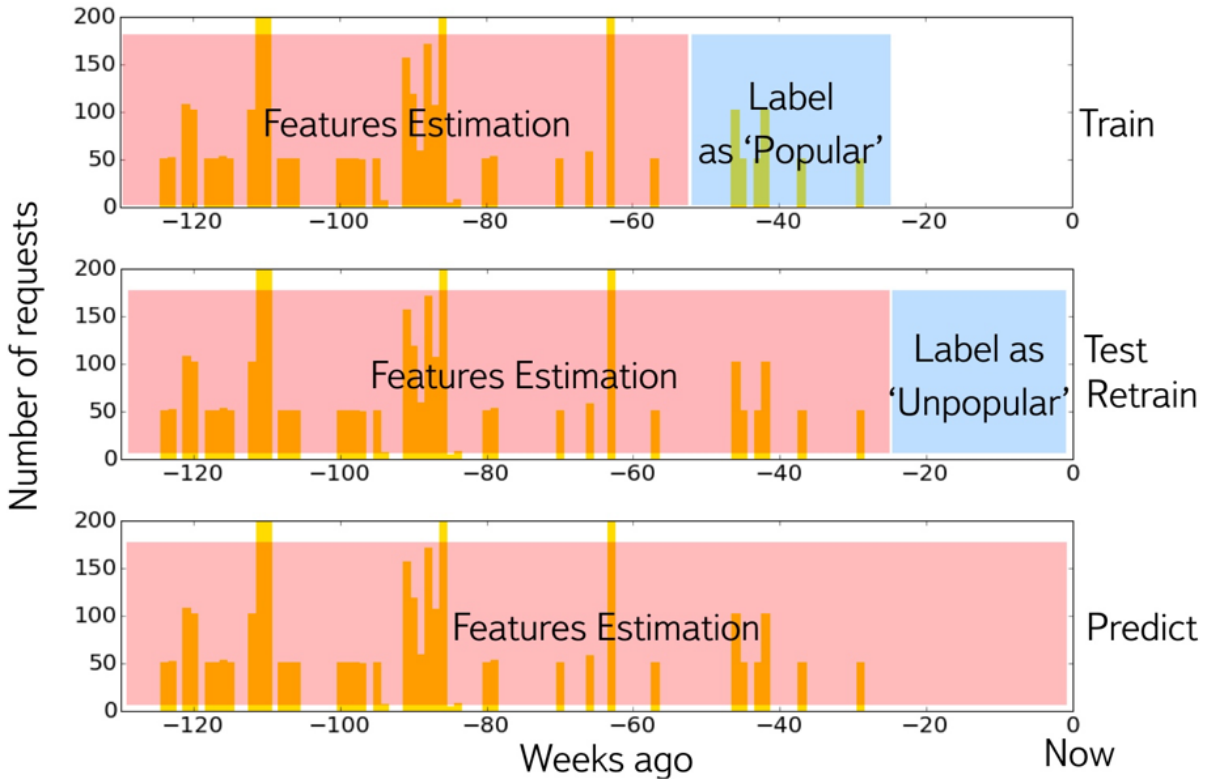
Long-Term Prediction

Use binary classification to predict that a dataset will be used in future period of time.

Datasets Labels:

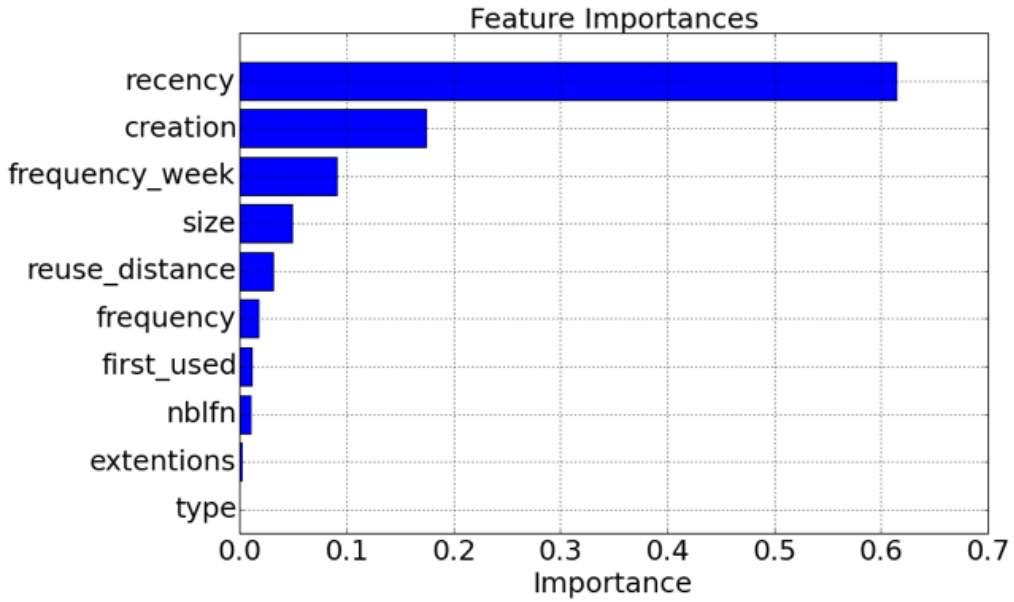
- Popular: will be used during the next 6 months
- Unpopular: otherwise

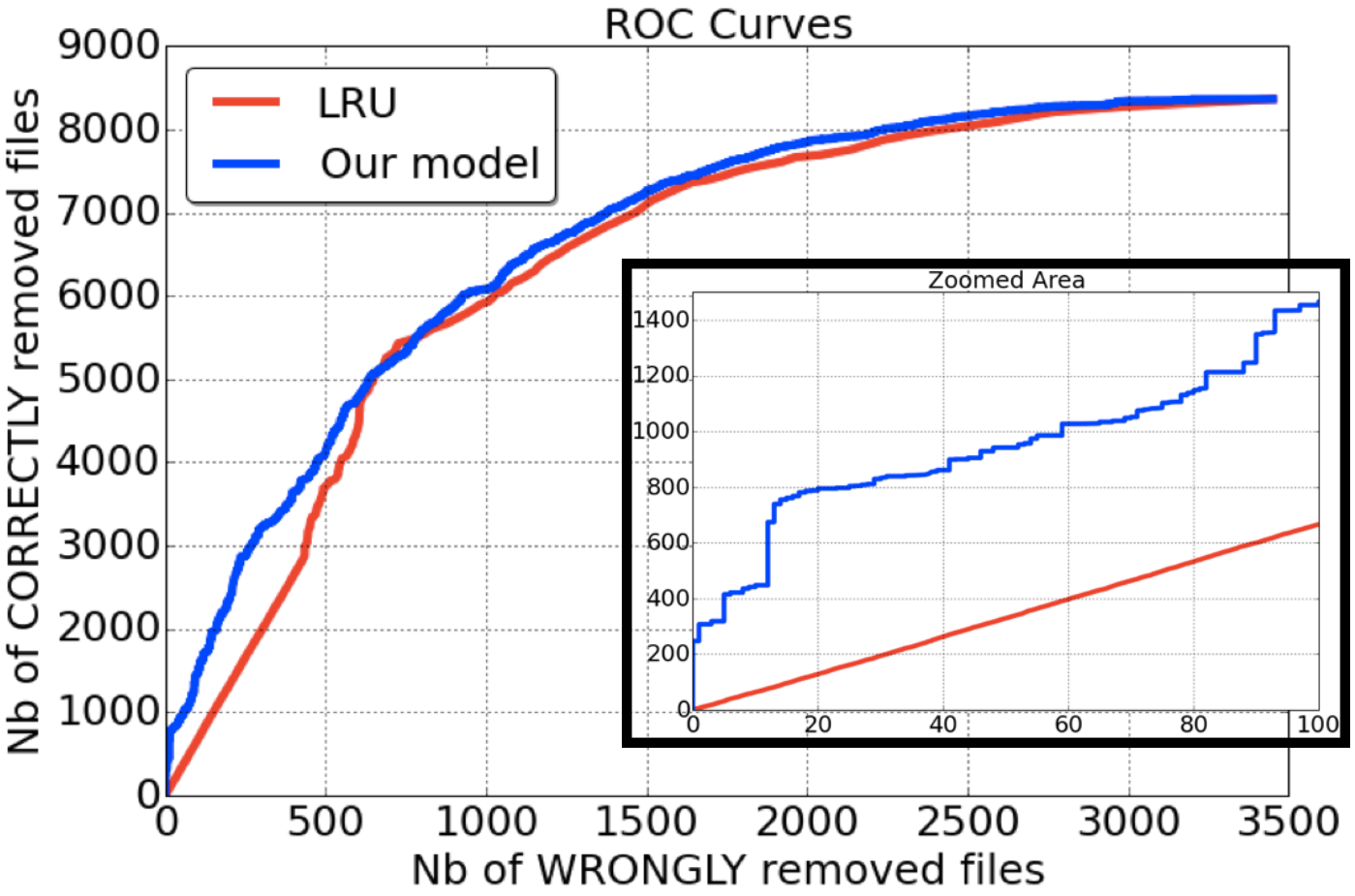
Input Features: recency, reuse distance, time of the first access, creation time, access frequency, type, extension and size.



Long-Term Prediction

The model is compared with Least Recently Used (LRU) algorithm.





Based on the classifier output, our model allows to remove more datasets from the disks correctly than LRU with the same number of mistakes.

Short-Term Forecast

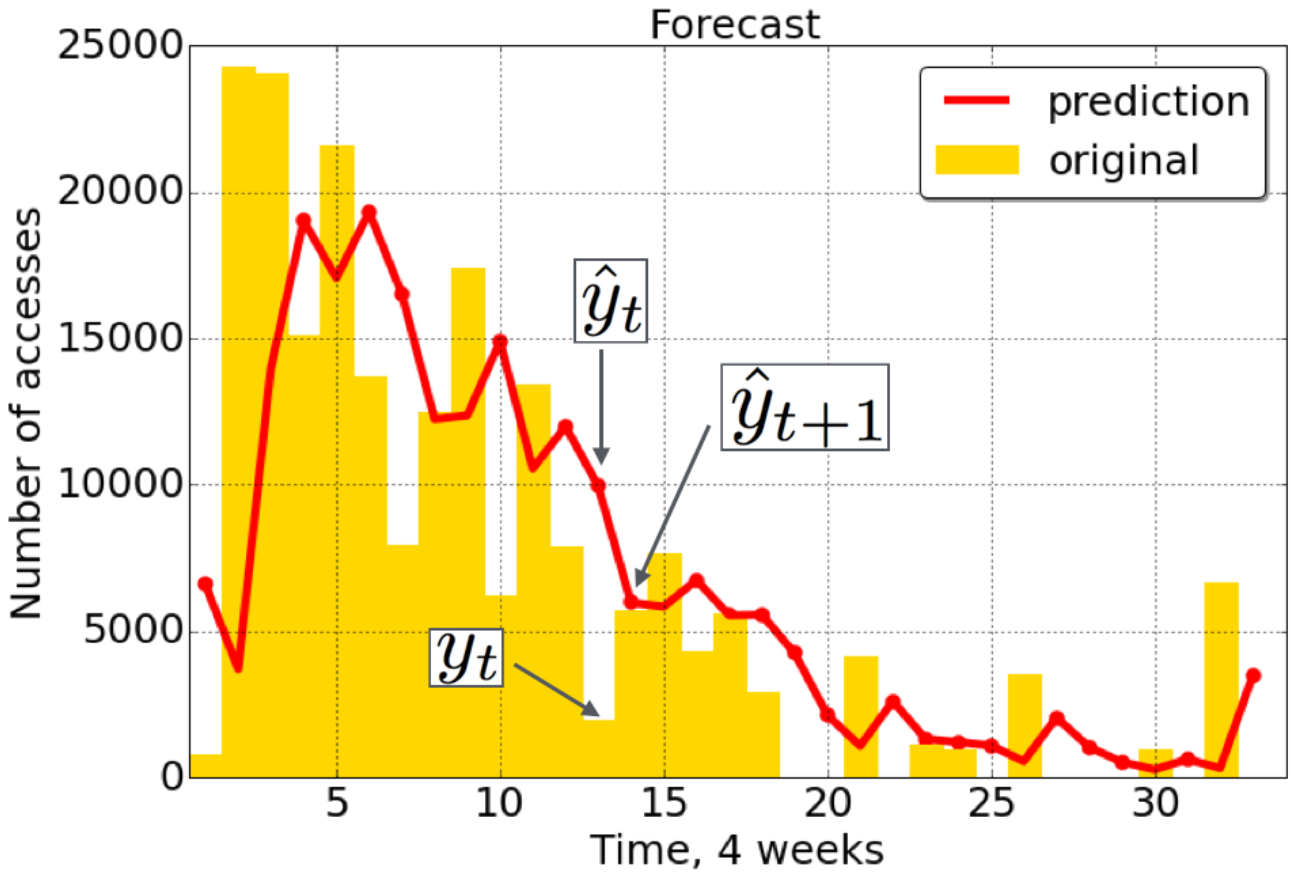
For datasets usage prediction Brown's simple exponential smoothing model was used.

The model is defined as:

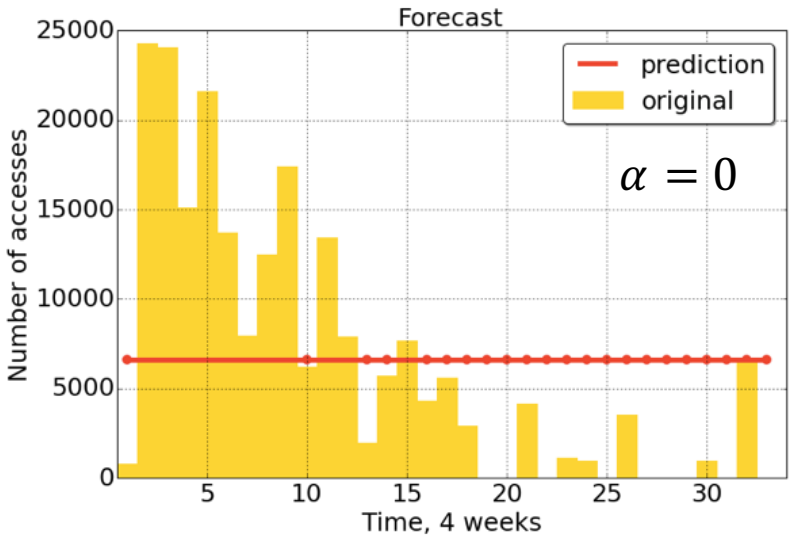
$$\hat{y}_{t+1} = \hat{y}_t + \alpha(y_t - \hat{y}_t)$$

$$\alpha = argmin \sum_t (\hat{y}_t - y_t)^2$$

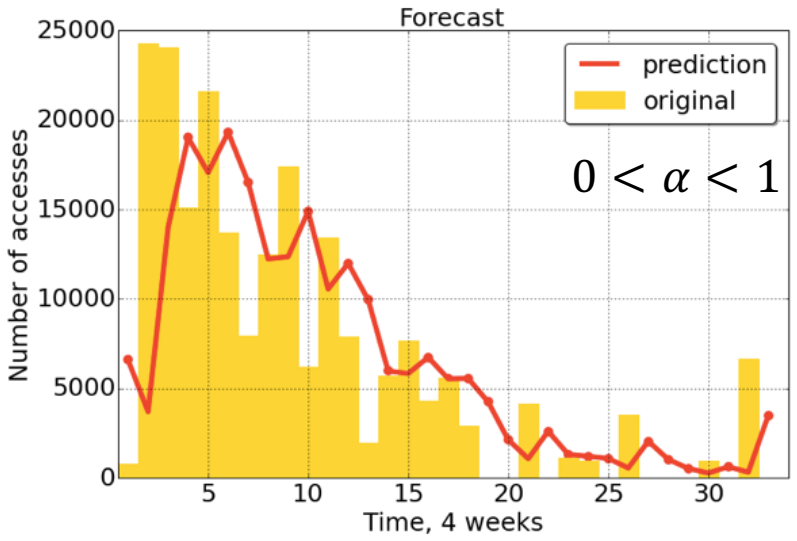
$$\hat{y}_0 = \frac{1}{n}\sum_{i=0}^{n} y_i, \quad \alpha \in (0,1)$$



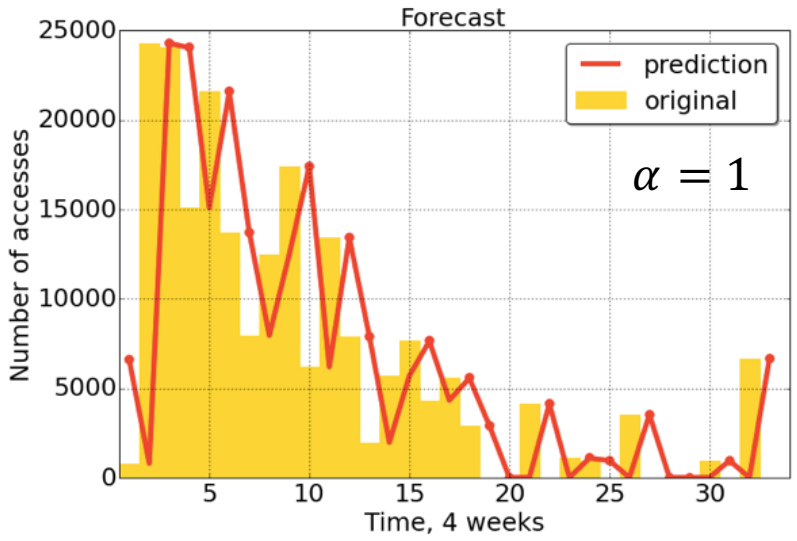
Short-Term Forecast



Average model



Optimal model



Static model

Replication Strategy

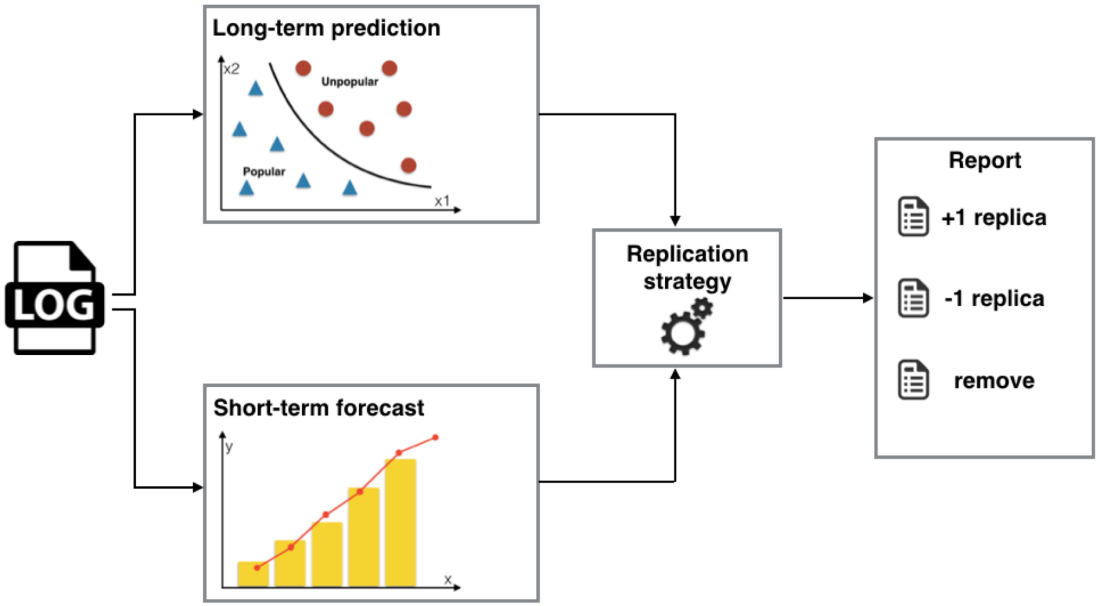
For each dataset calculate the metric M:

$$M = \frac{\hat{y}_t}{N_{replicas}}$$

To save disk space:
1. Remove 1 replica for a dataset with the minima M
2. Recalculate the M
3. Repeat steps 1-2.

This will remove replicas for less popular datasets.

Use long-term prediction is used to remove datasets from disks to tapes



Conclusion

- Automation in Data Management with Data Popularity:
  - Optimal number of datasets replicas estimation
  - Transfer to cold storage (tapes) decision

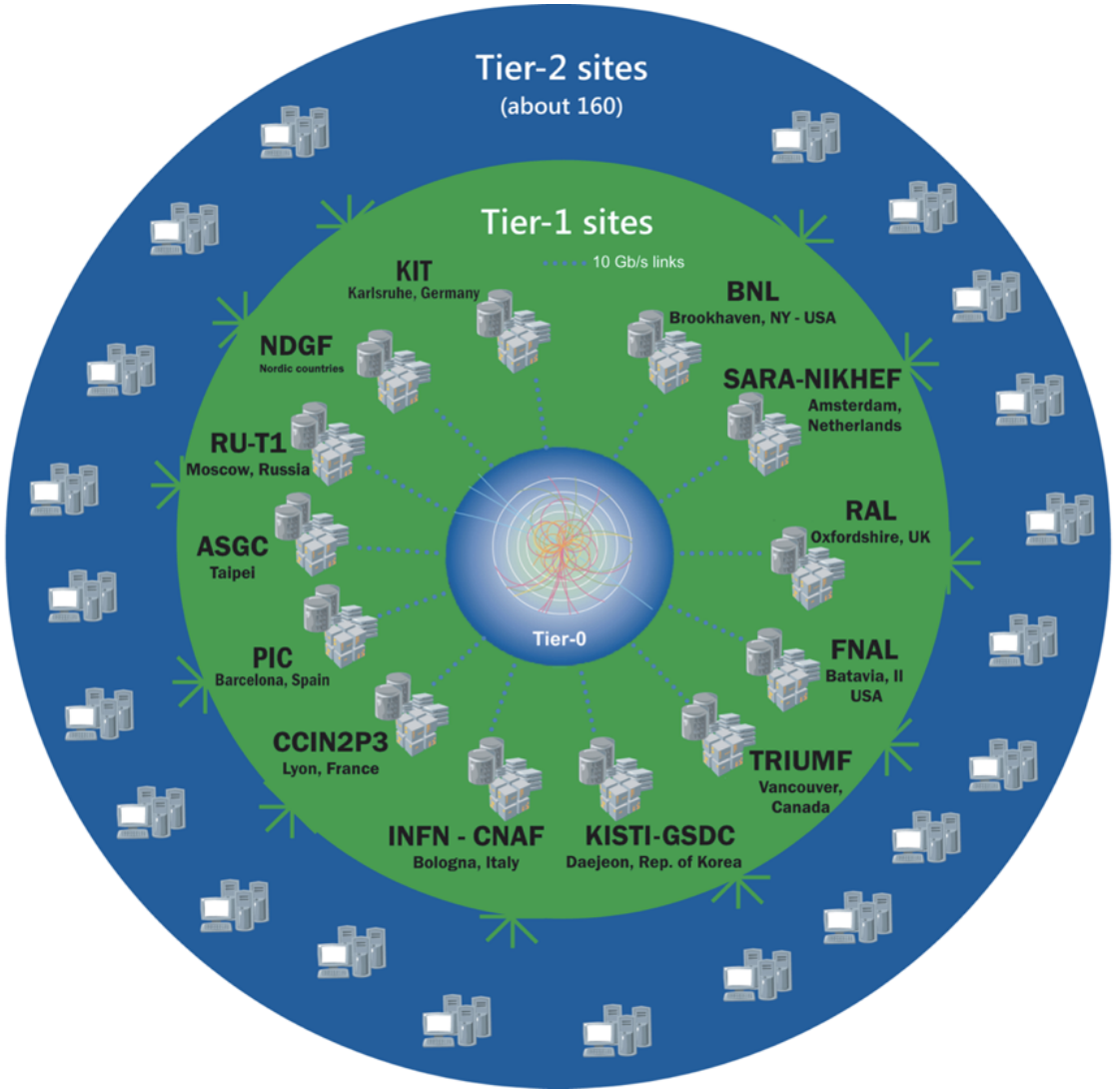
- It is used at LHCb since 2016

Paper: https://iopscience.iop.org/article/10.1088/1742-6596/898/6/062023

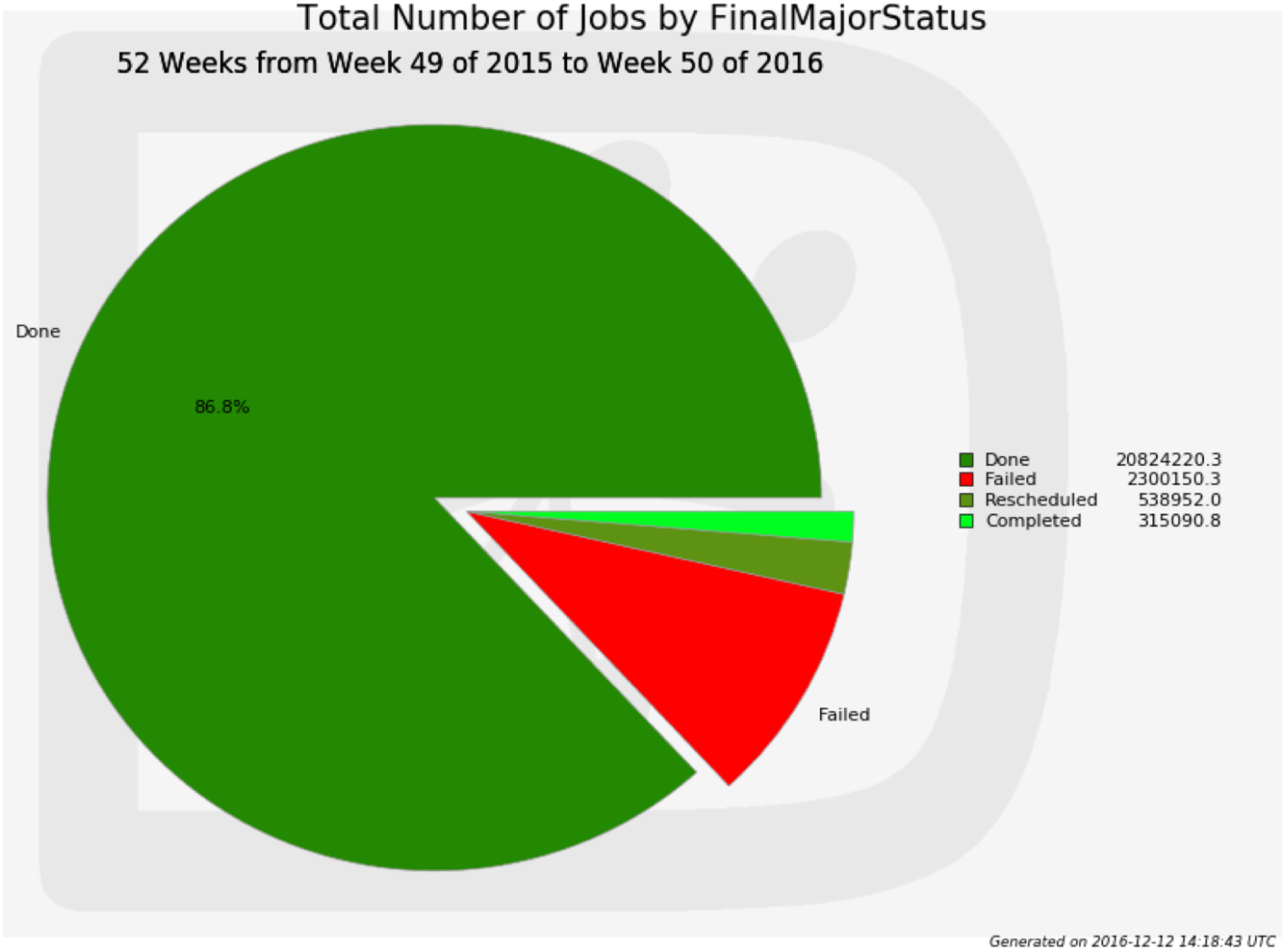
Production Monitoring Automation

WLCG

The Worldwide LHC Computing Grid (WLCG) is a global computing infrastructure whose mission is to provide computing resources to store, distribute and analyse the data generated by the LHC, making the data equally available to all partners, regardless of their physical location. WLCG is the world's largest computing grid.



LHCb in WLCG



http://lhcb-portal-dirac.cern.ch

LHCb Production Shifter's Duty

Failed Jobs:

- Monitor the overall job success rate for all production jobs.
- If jobs start failing at a single site, then it may be that a problem has arisen at that site.
- If jobs start failing at all sites then it is more likely to be a production or application misconfiguration.
- If there are lots of production jobs failing:
  - See what site the problem is connected with?
  - Are the failures in reconstruction or merging?
  - Are the failures associated with an old current production?
  - Are the failures re-tries associated with some site which has a known problem?

https://twiki.cern.ch/twiki/bin/view/LHCb/ProductionShifterGuide
https://twiki.cern.ch/twiki/bin/view/LHCb/UpdatedProductionShifterGuide

LHCb Production Shifter’s Duty

Non-processing Jobs:

- Particular attention should be paid to jobs in the states ``Waiting'' and ``Staging''.
- Problematic jobs at this stage are easily overlooked since the associated problems are not easily identifiable.

Non-Starting Jobs:

- Jobs arriving at a site but then failing to start have multiple causes.

https://twiki.cern.ch/twiki/bin/view/LHCb/ProductionShifterGuide
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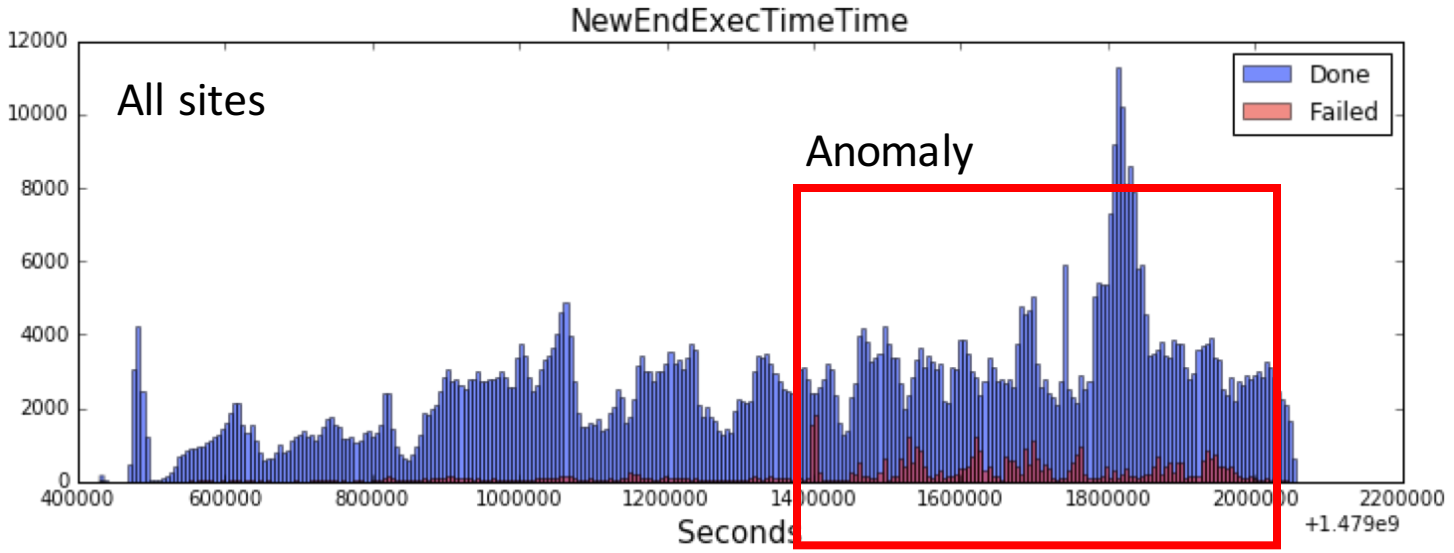
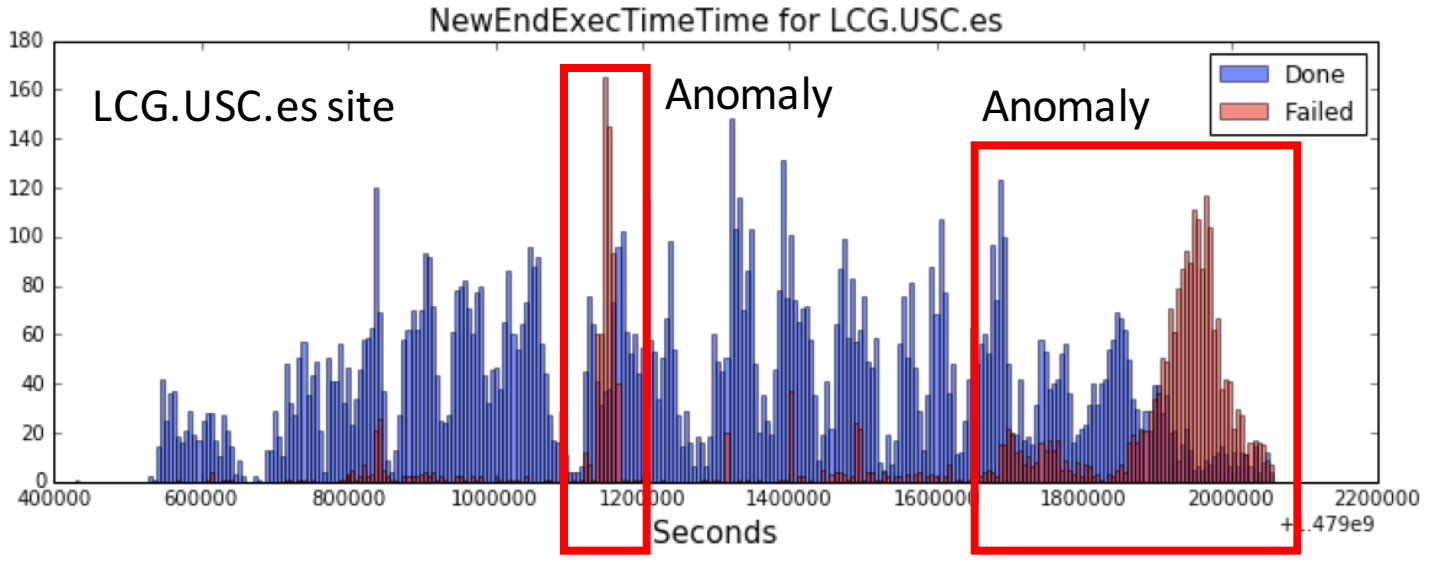
Examples

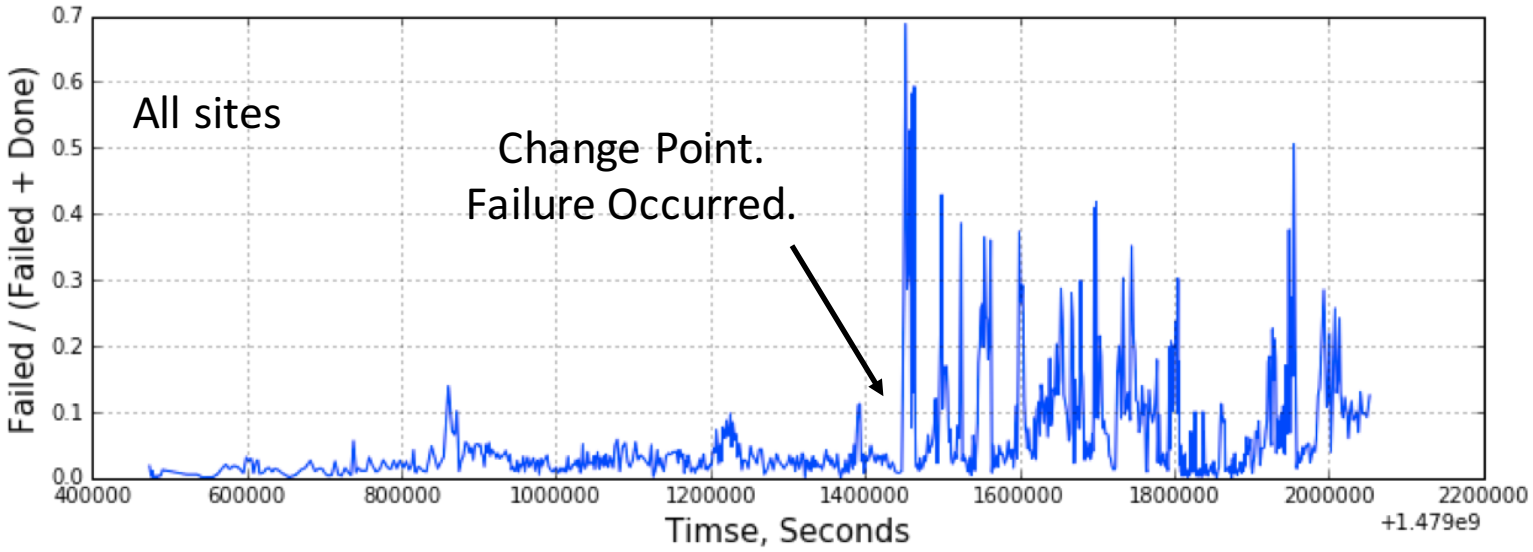
- Significant deviation of number of failed jobs is considered as anomaly.
- Anomaly is a result of a system failure.





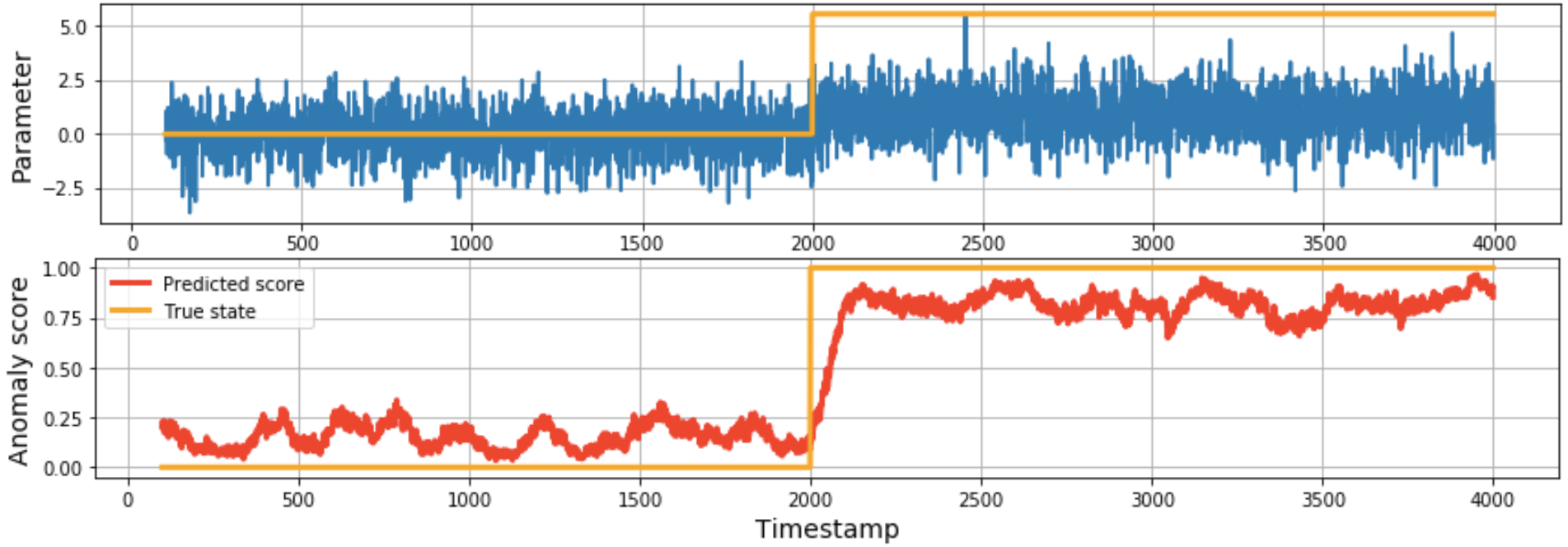
Failure Detection in Time Series

- Anomalous and normal states have different distributions of their parameters
- Failure detection means detection of the distributions changes
- This problem is known as change point detection problem in time series.



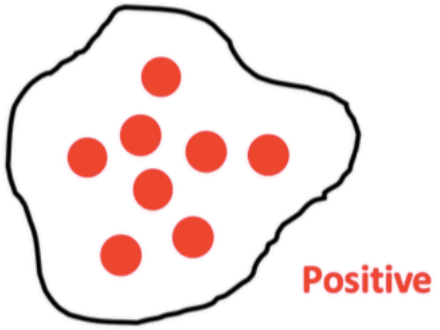
Binary Classification

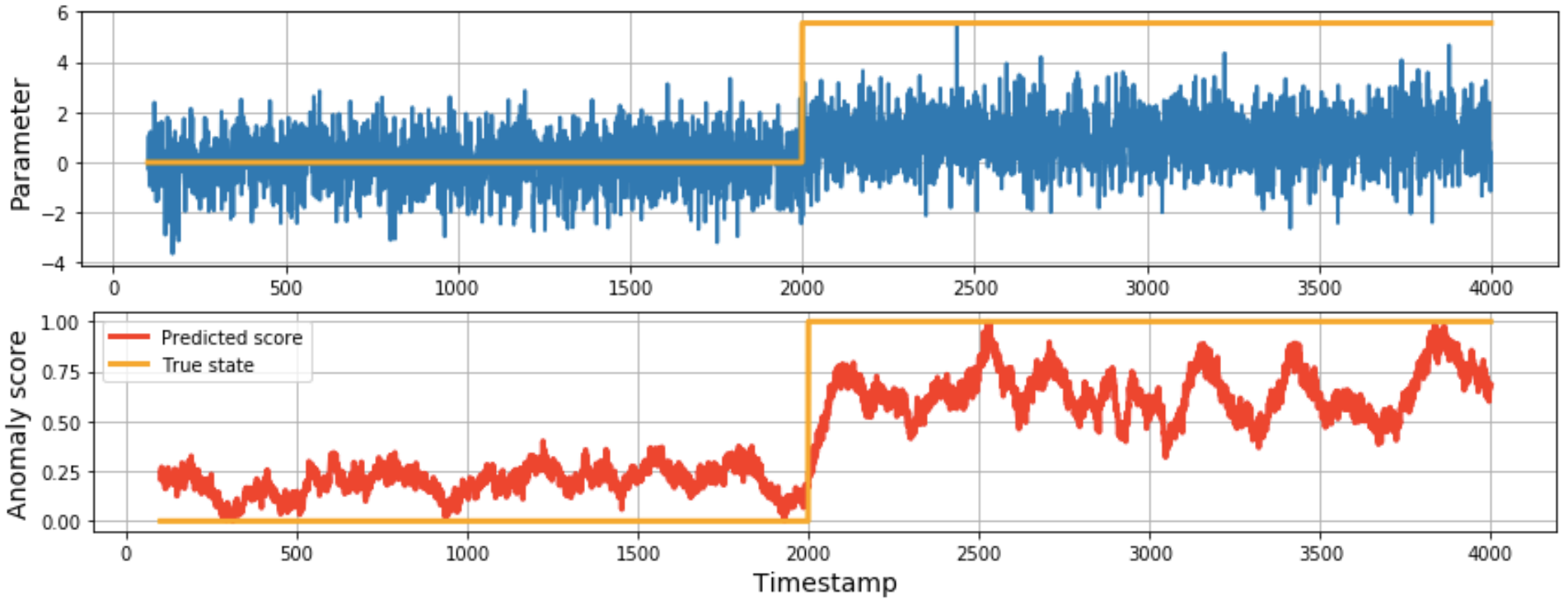
- The method supposes that normal and anomalous states form two classes.
- The classifiers learn separation surface between the two classes.
- They need information about anomalies
- The best detection quality



One-class Classification

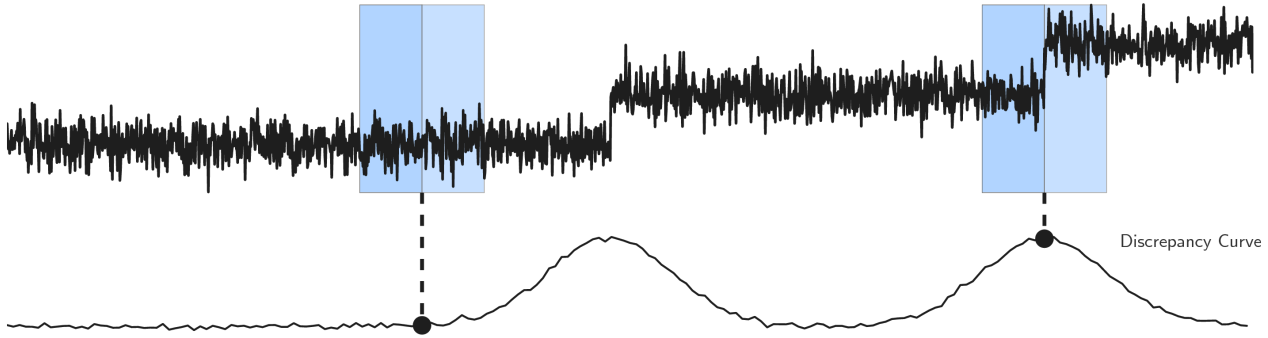
- The method supposes that normal states form a class.
- It learns the normal class boundaries.
- Everything outside is anomaly.
- Information about anomalies is advised but not required
- The lowest detection quality

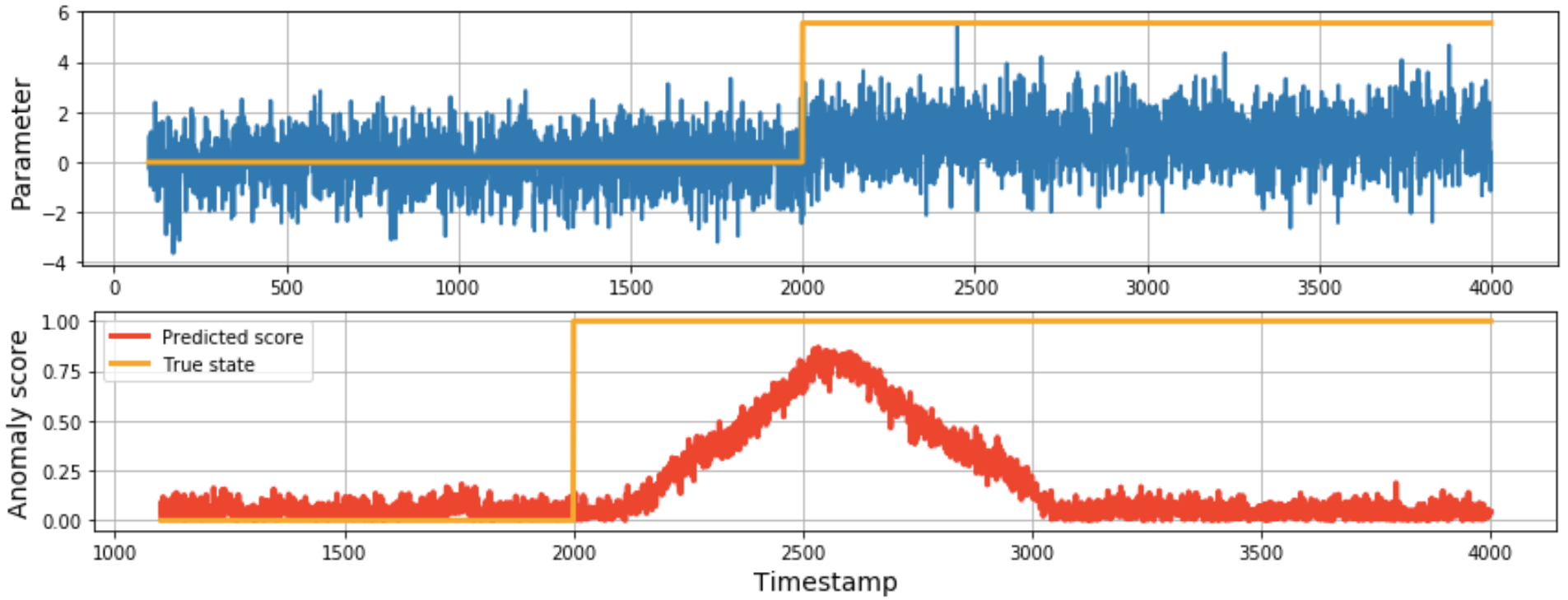




Change Point Detection

- Compare two consecutive windows
- Two windows == two classes
- Separate the classes using binary classifiers
- Measure the classification quality
- Does not need information about anomalies
- High detection quality





Conclusion

- Automation in WLCG monitoring with Change Point Detection:
  - Sites failures detection
  - Production software failures detection

- Other projects in Operational Intelligence:
  - LHCb detector and HLT monitoring & DQ
  - CMS offline Data Quality (https://iopscience.iop.org/article/10.1088/1742-6596/898/9/092041)
  - Digital Twins for Data Storage System automation (https://doi.org/10.25728/assa.2018.18.4.660)