Predictive Maintenance and Anomaly Detection for Wind Energy

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April 12, 2022

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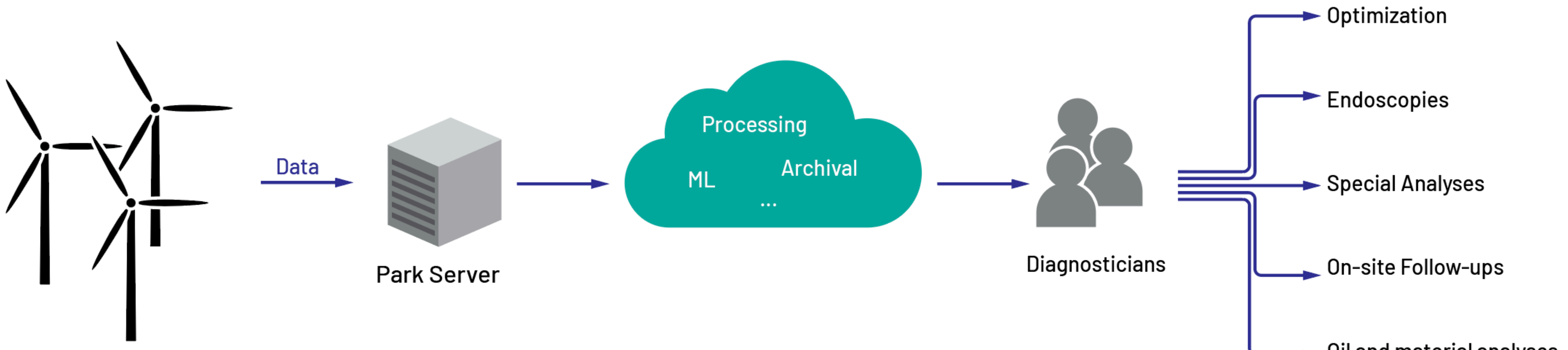
Condition Monitoring at EnBW: Asset RADAR

CURRENT STATE

- Monitoring of ~450 Wind Turbines in Germany and other parts of Europe
- Monitoring of all relevant components
- Multiple detection methods
- Bundled in proprietary software
- Alerts created are reviewed by diagnosticians

OBJECTIVES

- Monitoring of all units operated by EnBW (also including e.g. solar)
- Minimize on-site maintenance by technicians
- Usage of all data to ensure interventions as early as possible
- Continuous development and improvement

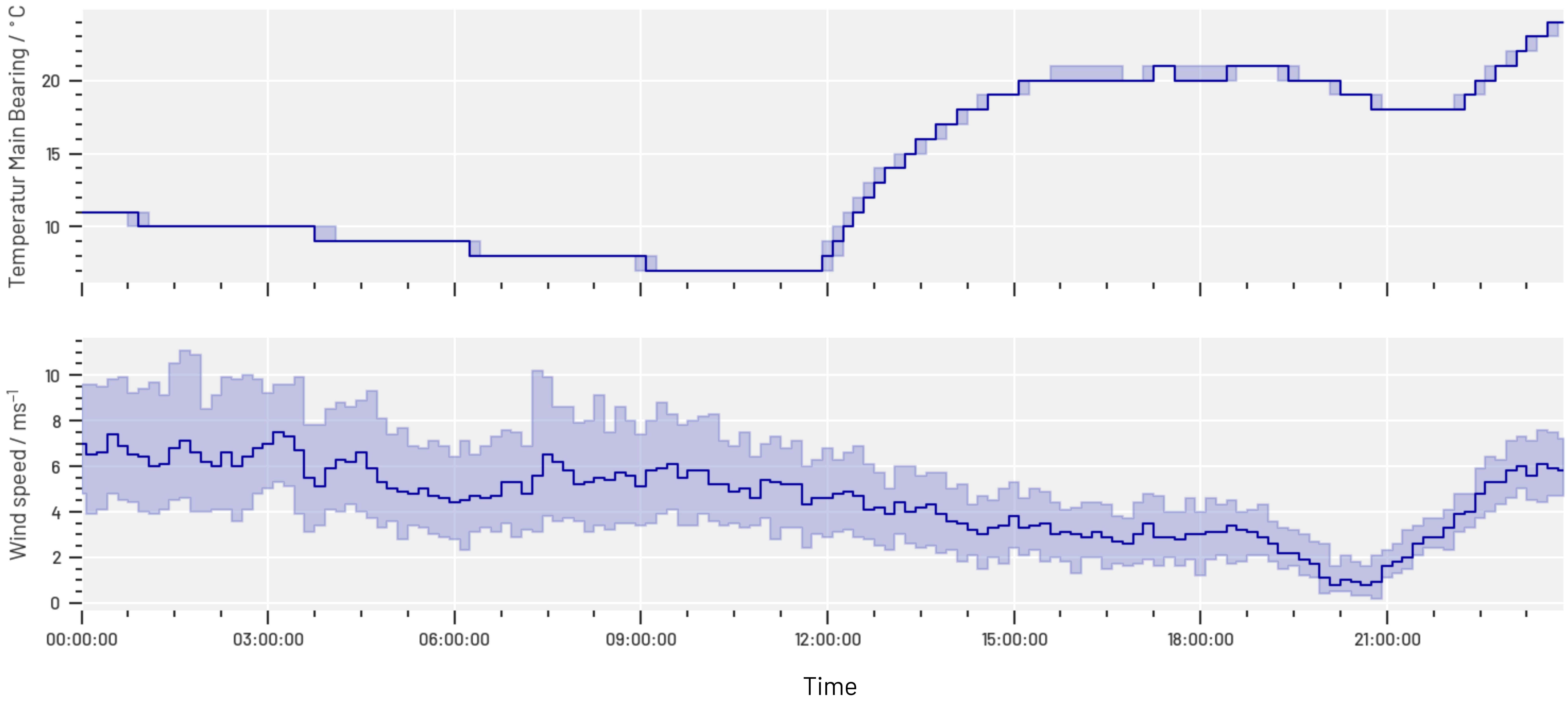


Condition Monitoring at EnBW: Data Sources

SUPERVISORY CONTROL AND DATA ACQUISITION (SCADA)

- Data continuously collected from sensors
  - Temperatures
  - Pressures
  - Currents
  - ...
- Data aggregated in 10 minute intervals
  - Mean
  - Maximum
  - Minimum
  - Standard Deviation

Condition Monitoring at EnBW: SCADA



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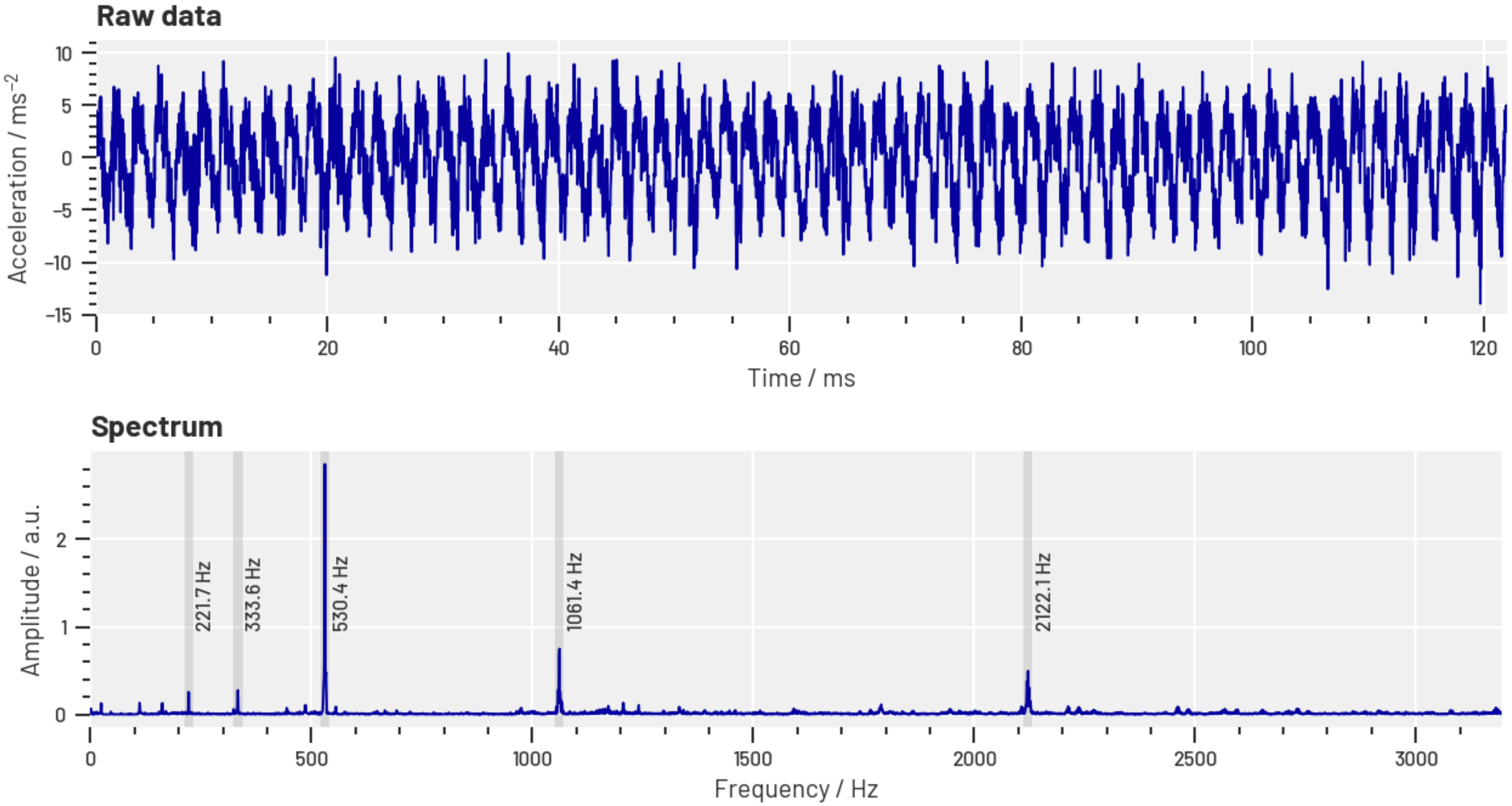
OSCILLATION DATA

- Acceleration data collected from multiple sensors in different locations on the drive train
- Not measured continuously, but in irregular intervals
- High sampling rate (up to 50 kHz), short “clips” of data
- Allows for highly specific analysis of individual defect patterns

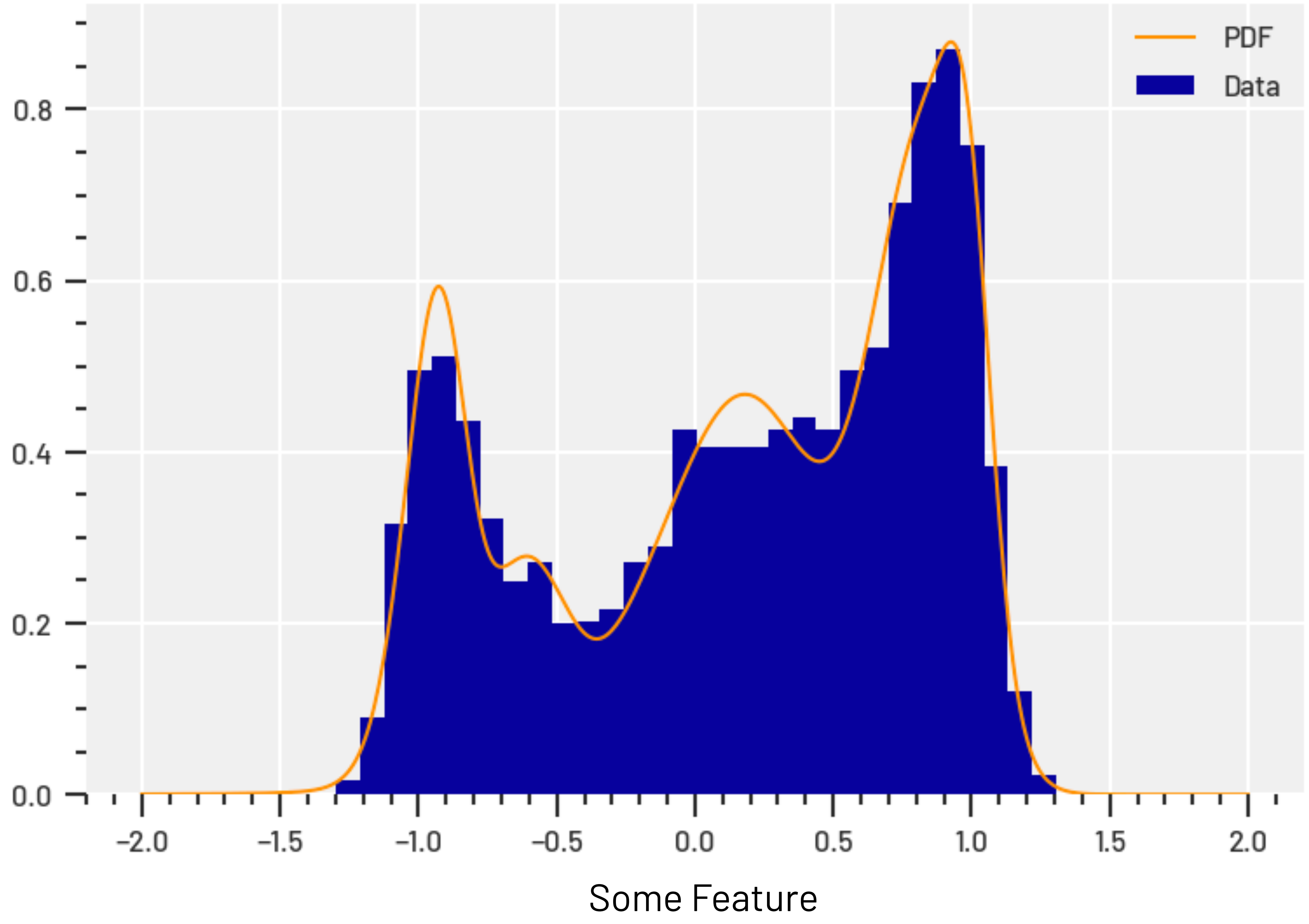
Condition Monitoring at EnBW: Oscillation



Anomaly Detection

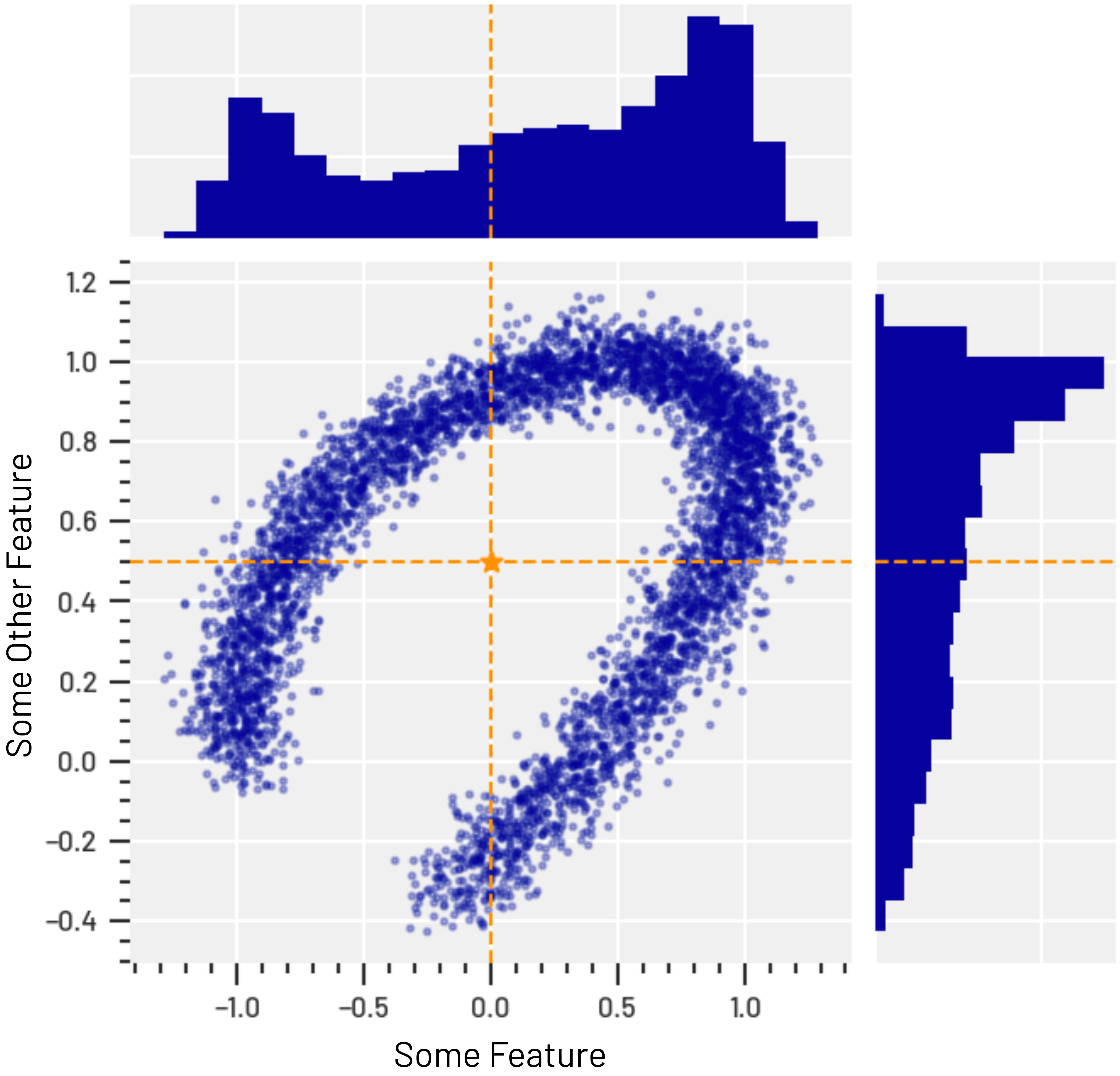
DEFINITION OF ANOMALY

- An observation that can be considered significantly outside what is “normal”
- Requires some idea what constitutes “normal”
- That is very much non-trivial
- Statistically: Given input data X, an anomaly is a sample with a low value for its pdf, $p(X)$
- Calculating p, incidentally, is also very much non-trivial



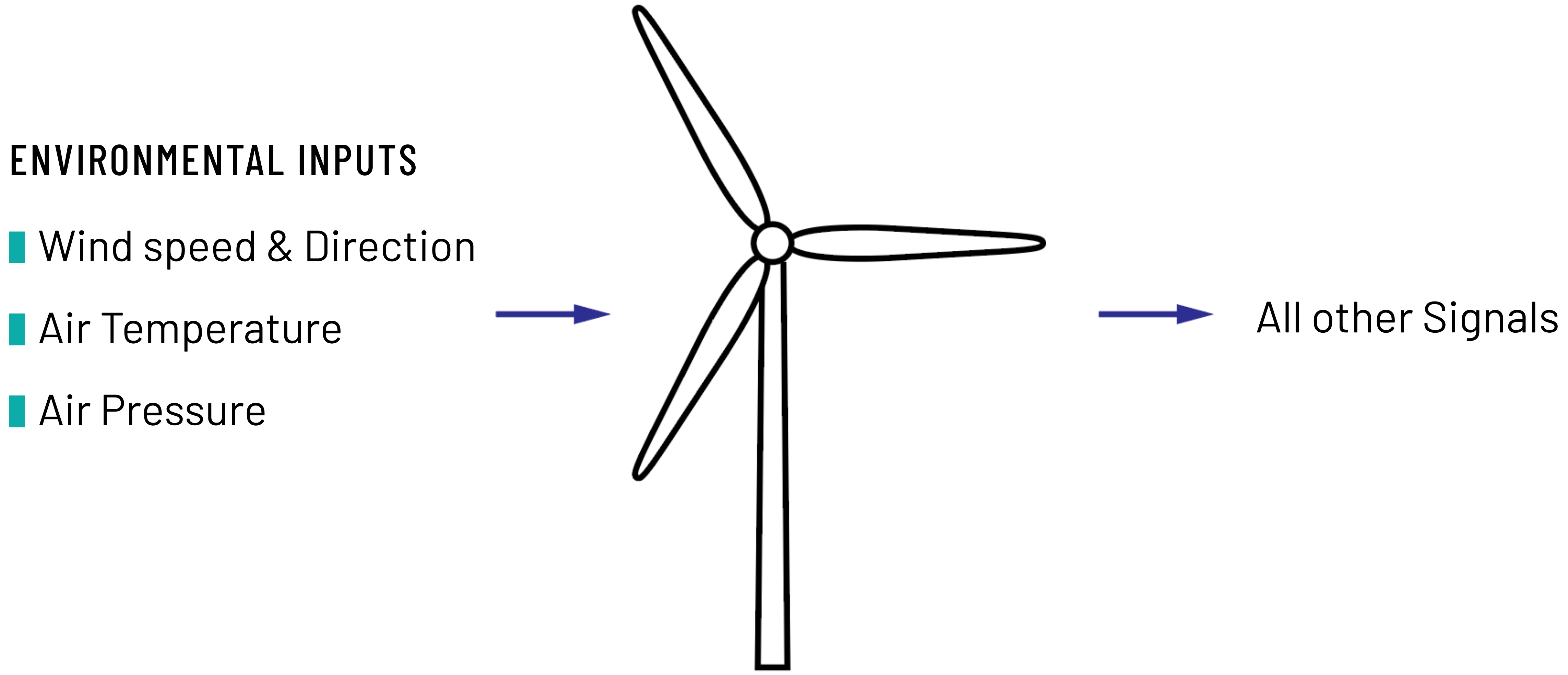
Anomaly Detection: Some More Complications

- Multivariate anomalies: data that does not look suspicious from any univariate point of view, may still be anomalous
- The higher the dimensionality, the harder this gets
- Rate of anomalies is unknown
  - What exact value for *p* is sufficiently small?
  - How do we determine "normality" given data that may or may not be anomalous?
- Time series are especially difficult: samples are not independent variables



Predictive Modeling: Idea

- Expectation: in a healthy system, there should be robust relationships between states of components
- Example: the power output dominantly depends on wind speed and other environmental conditions
- Therefore, statistical modeling should deliver good predictions of first from the former
- Deviations can be explained by defects



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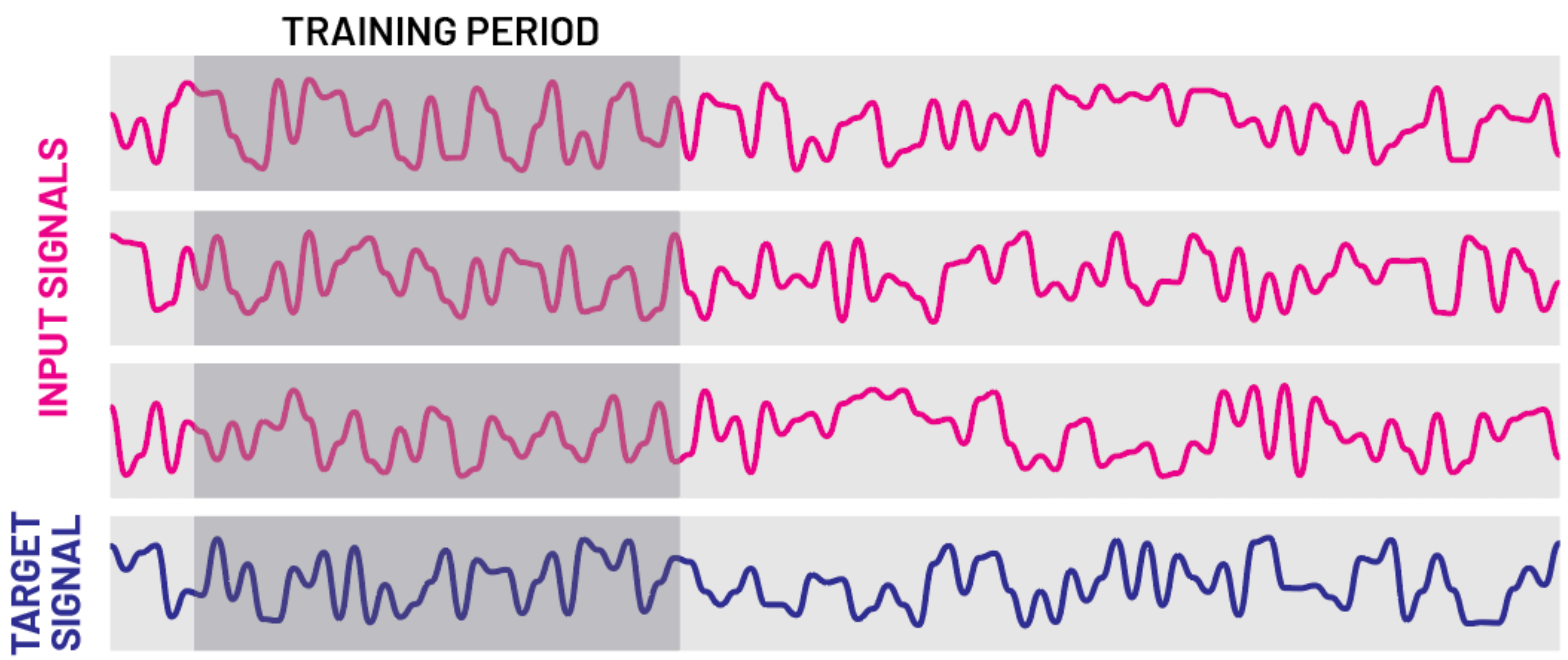

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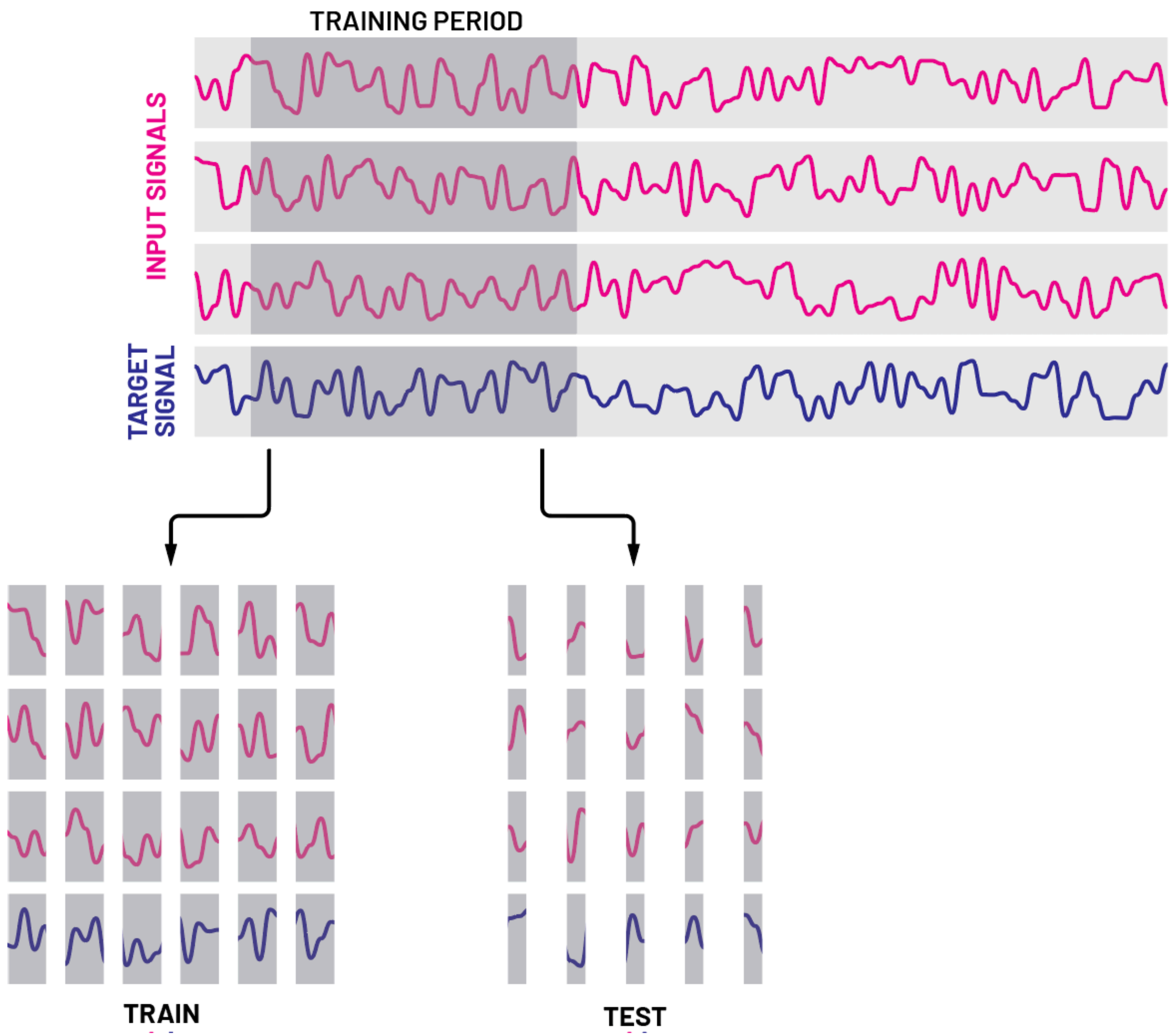

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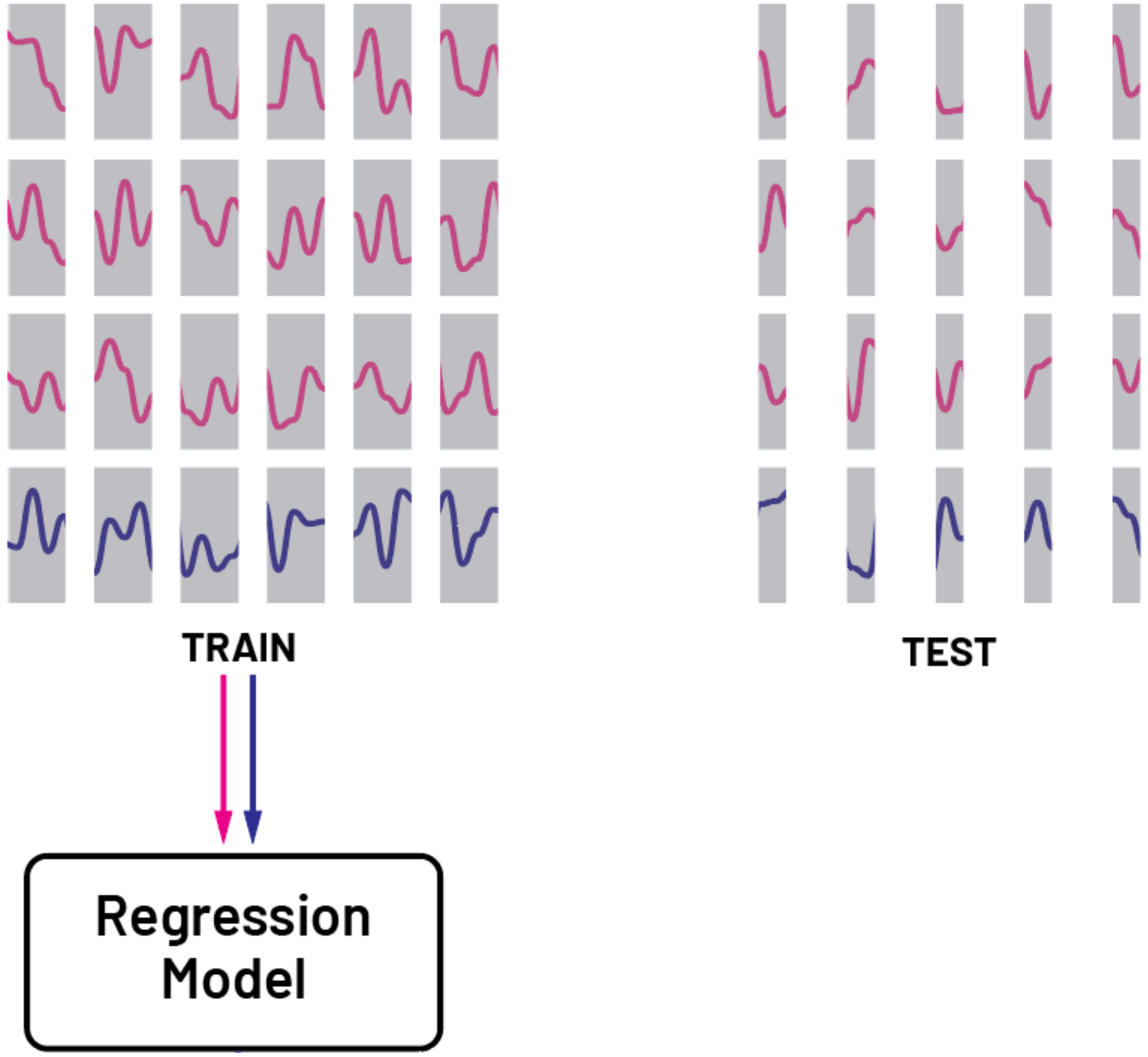

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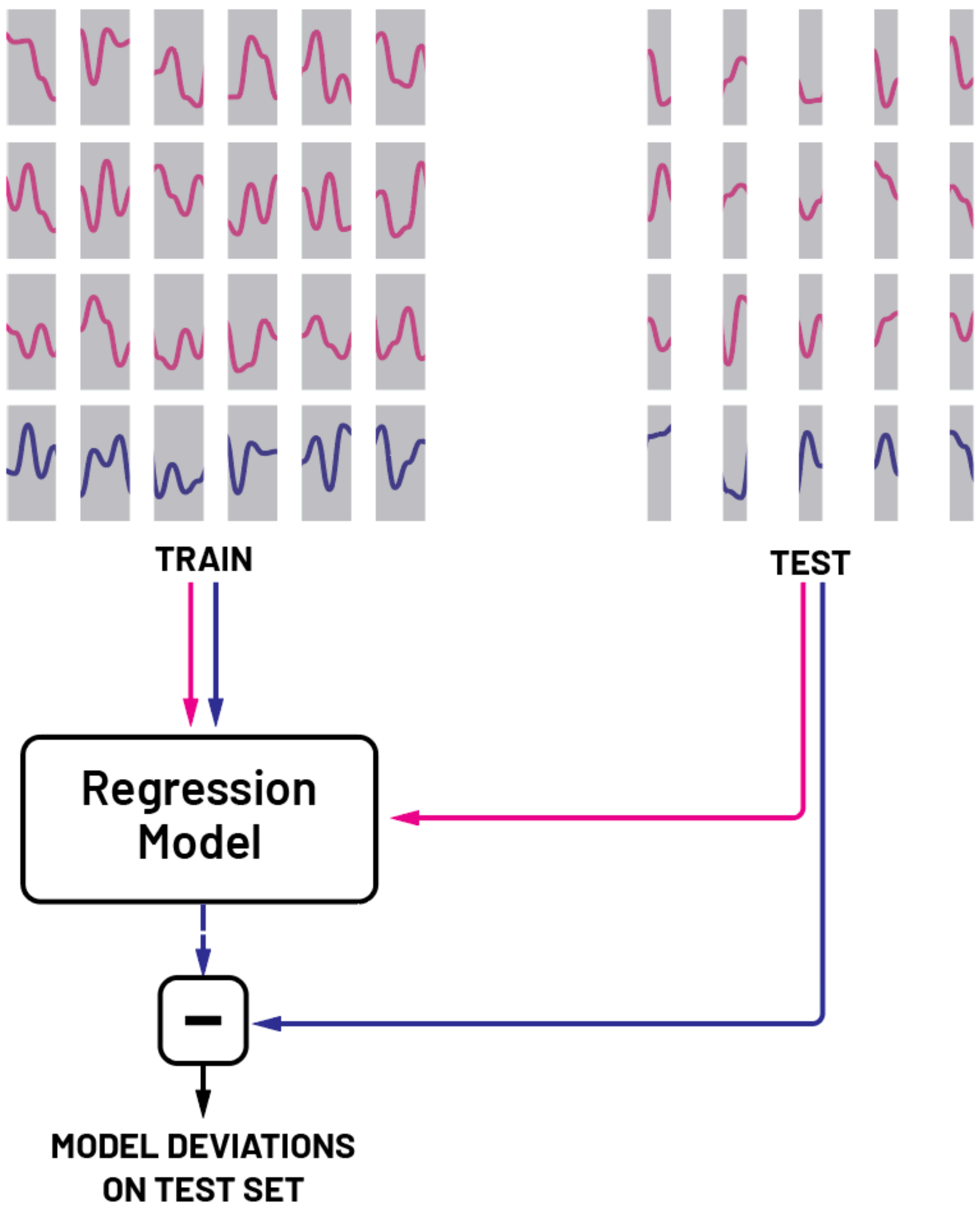
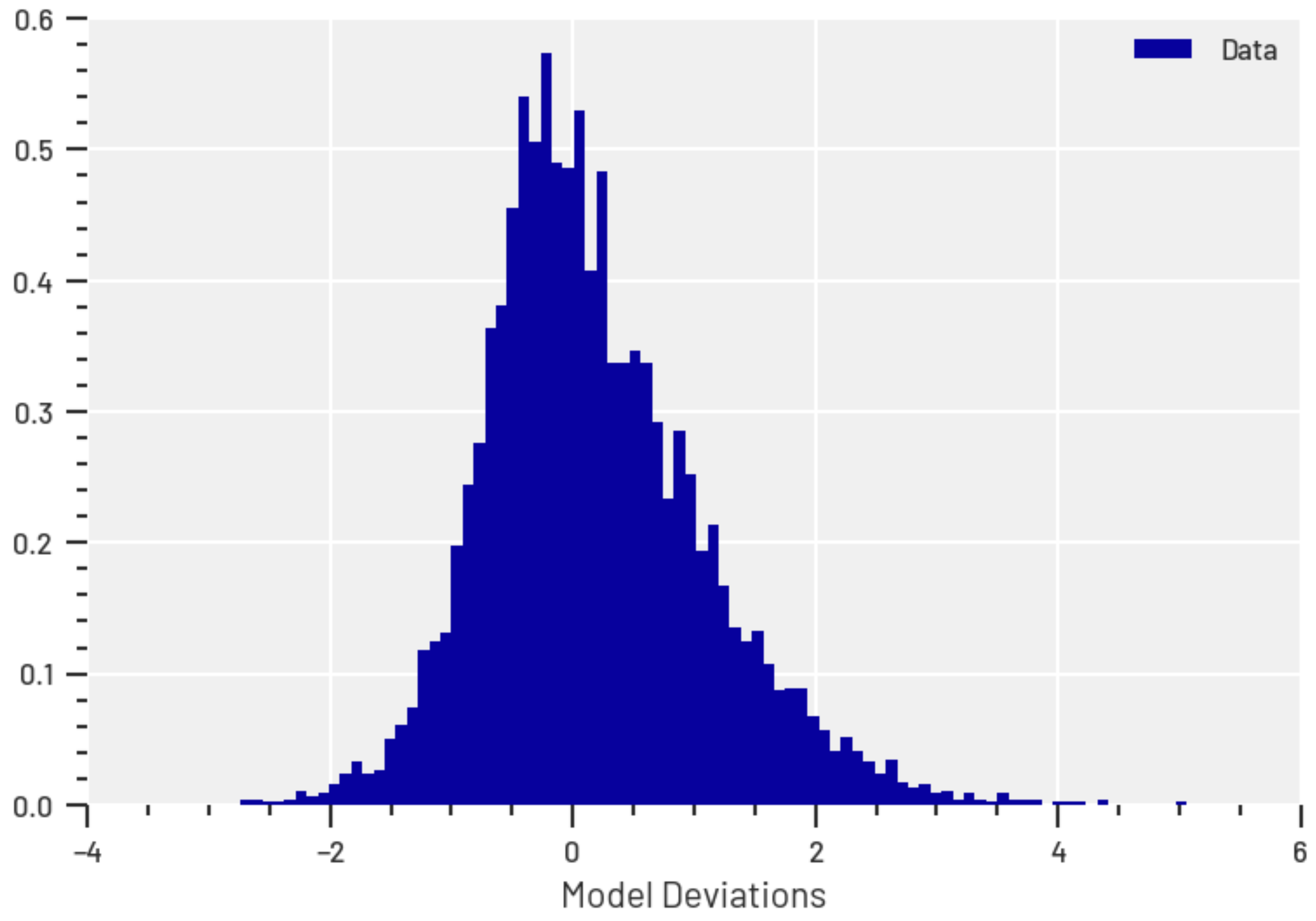


Predictive Modeling: Thresholds

- Arguably biggest challenge: when is a model deviation “unusual”?
- Model deviations in test set used as a gauge



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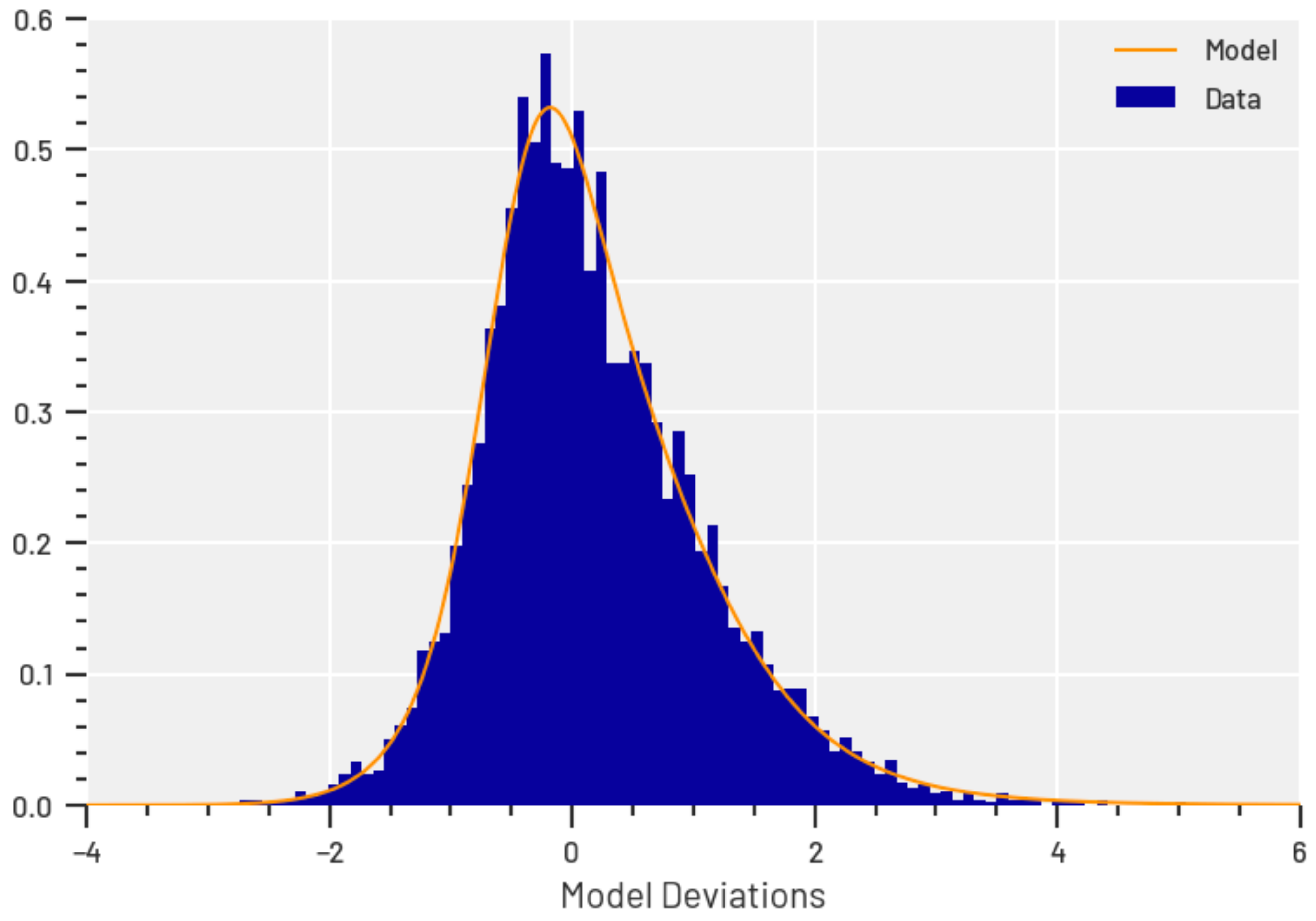

Predictive Modeling: Thresholds

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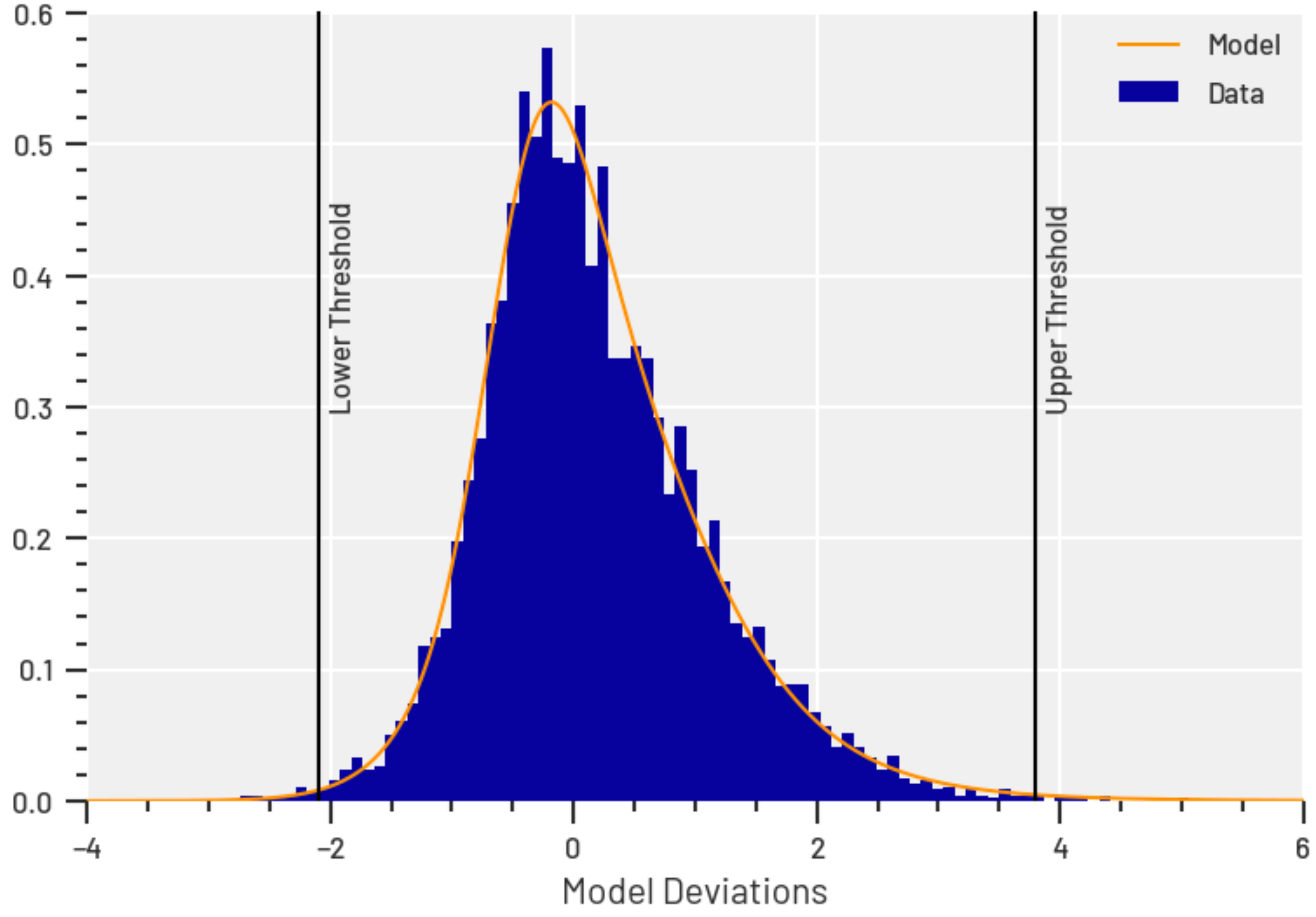
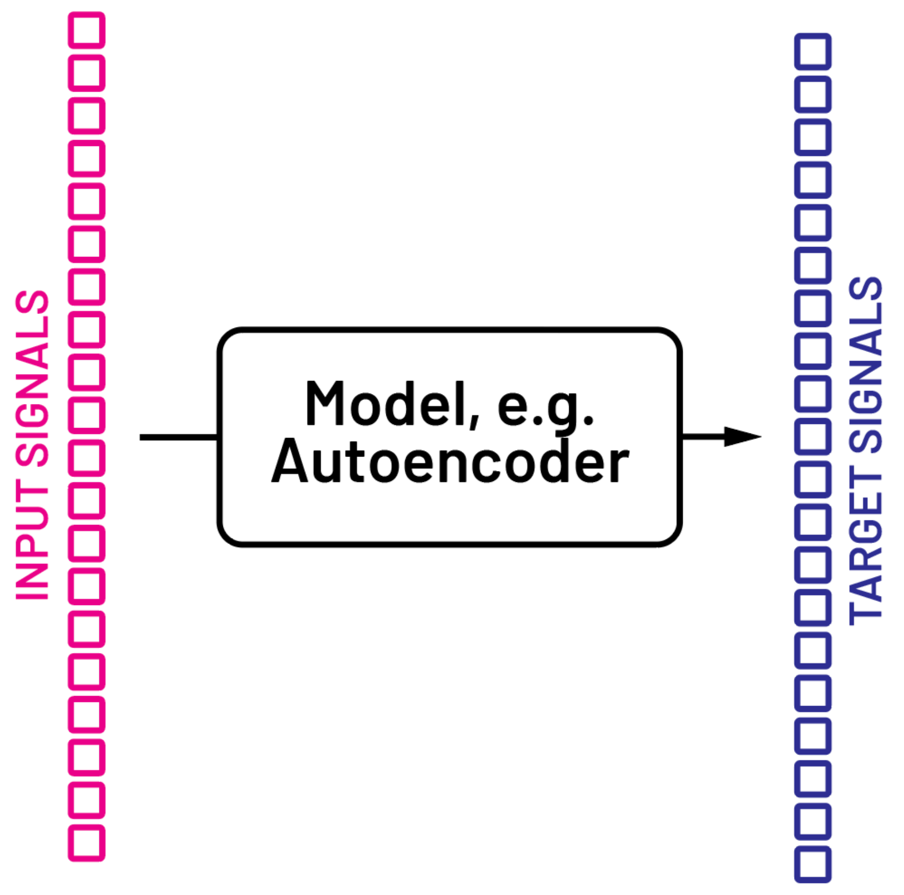
- Model deviations in test set used as a gauge
- Statistical modeling of distribution
- Some quantile of modeled distribution taken to be alert threshold



Predictive Modeling: Specific vs. Generic

VERY GENERIC MODELS THAT TAKE LOTS OF INPUTS

- Fewer models
- Complete monitoring
- Hard to interpret
- No use of engineering knowledge



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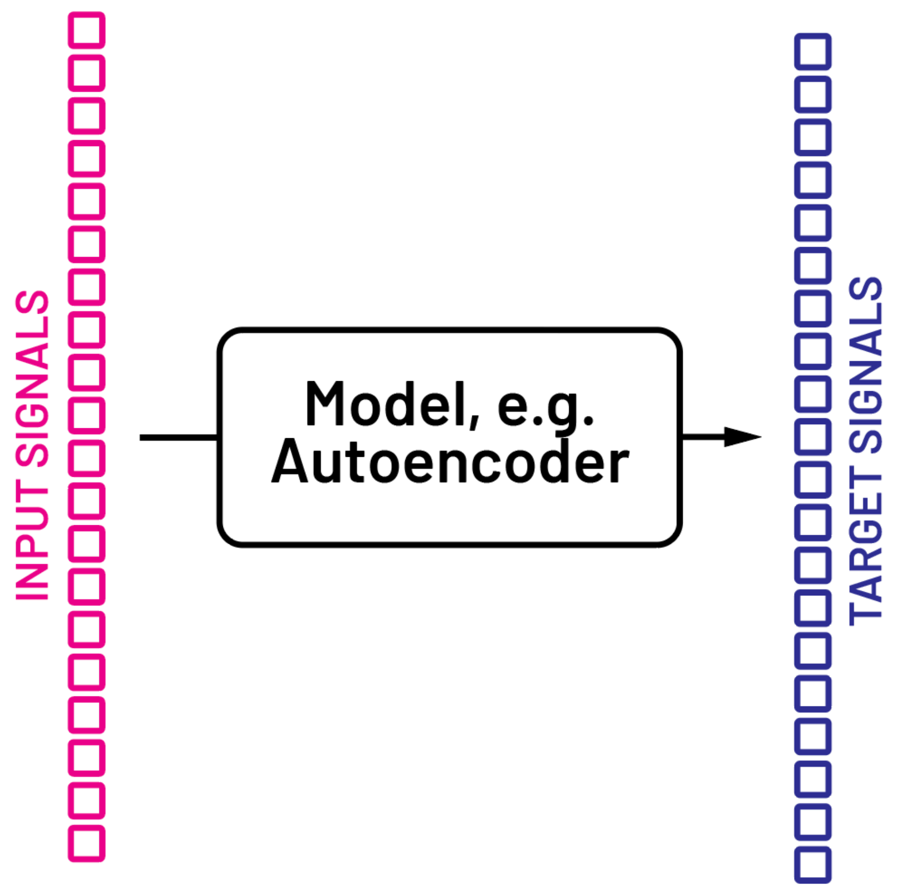

SPECIFIC MODELS WITH FEW INPUTS

- A *lot* of models
- Not every signal is necessarily monitored
- Each model indicates small set of diagnoses
- Engineering knowledge weaved into models

Future Plans: Automatic Diagnoses

- Future of wind energy: more units
- Scalability of maintenance: less manual work
- Models need to give more precise pointers to facilitate diagnoses
- Idea: Meta model that learns from previous diagnoses of defects

Challenges: Heterogeneity

Enercon
Vestas
Manufacturers
GE
Senvion
Siemens

10 min
1 s
10 Hz
Resolutions
50 kHz
24 kHz

Controllers

Gears
Generator
Components
Pitch system
Cooling System
Bearings

Ice Detection
Additional Systems
Structural Monitoring

V90
V126
Station Types
SWT-2.3-93
SWT-3.6-120

Oscillation
Data Sources
SCADA
Status Codes

Weather + Seasons

Challenges: Labels

- Incomplete labels
- Defects are actually very rare overall
- ~450 units
- ~7 years of average lifetime
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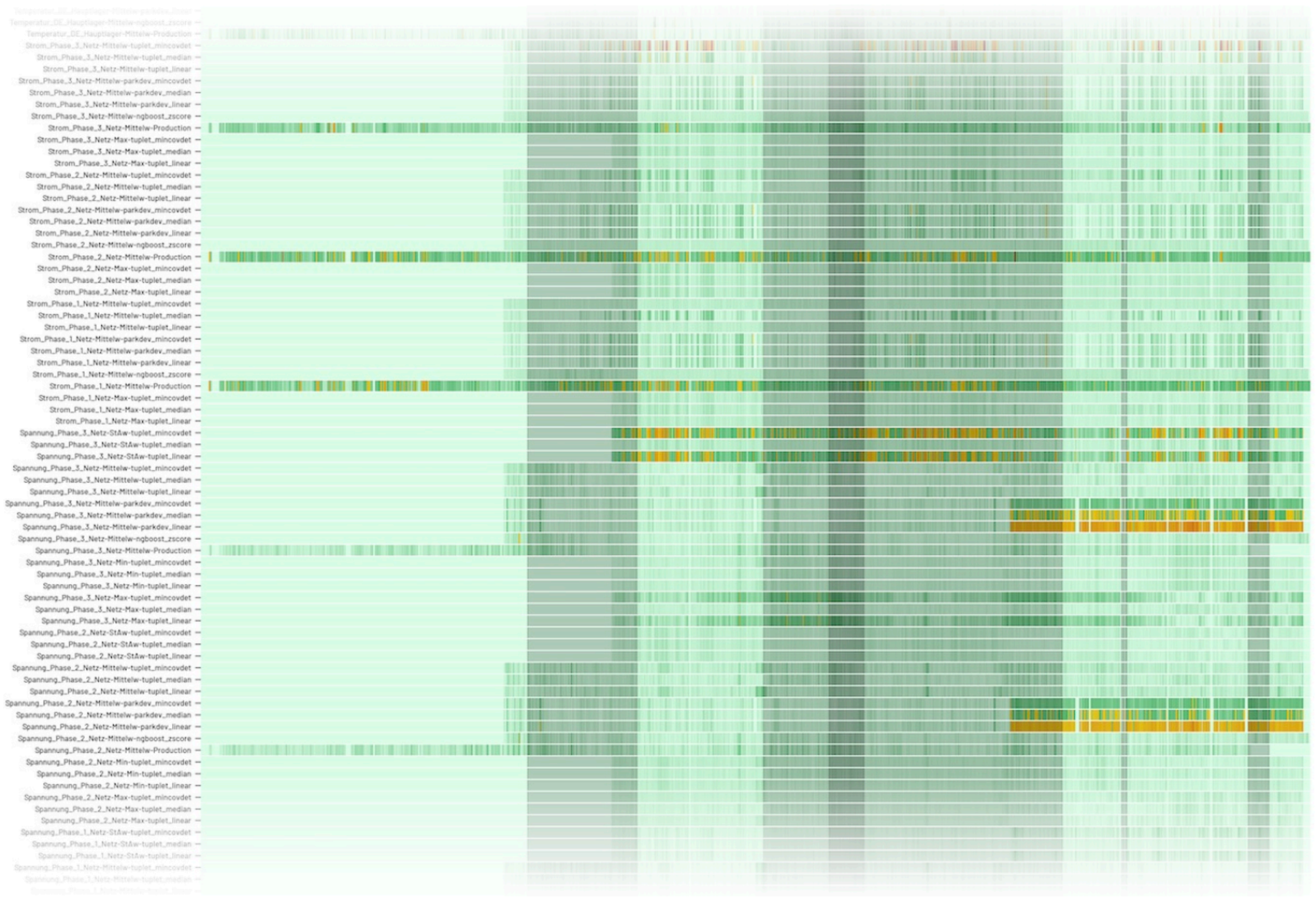
- Incomplete labels
- Defects are actually very rare overall
- ~450 units
- ~7 years of average lifetime
- ~80 monitored signals per unit on average
- 252,000 years of data (with 10 min resolution)
- 0.05% of which are labeled as exhibiting defects

Solutions: Anomaly Space

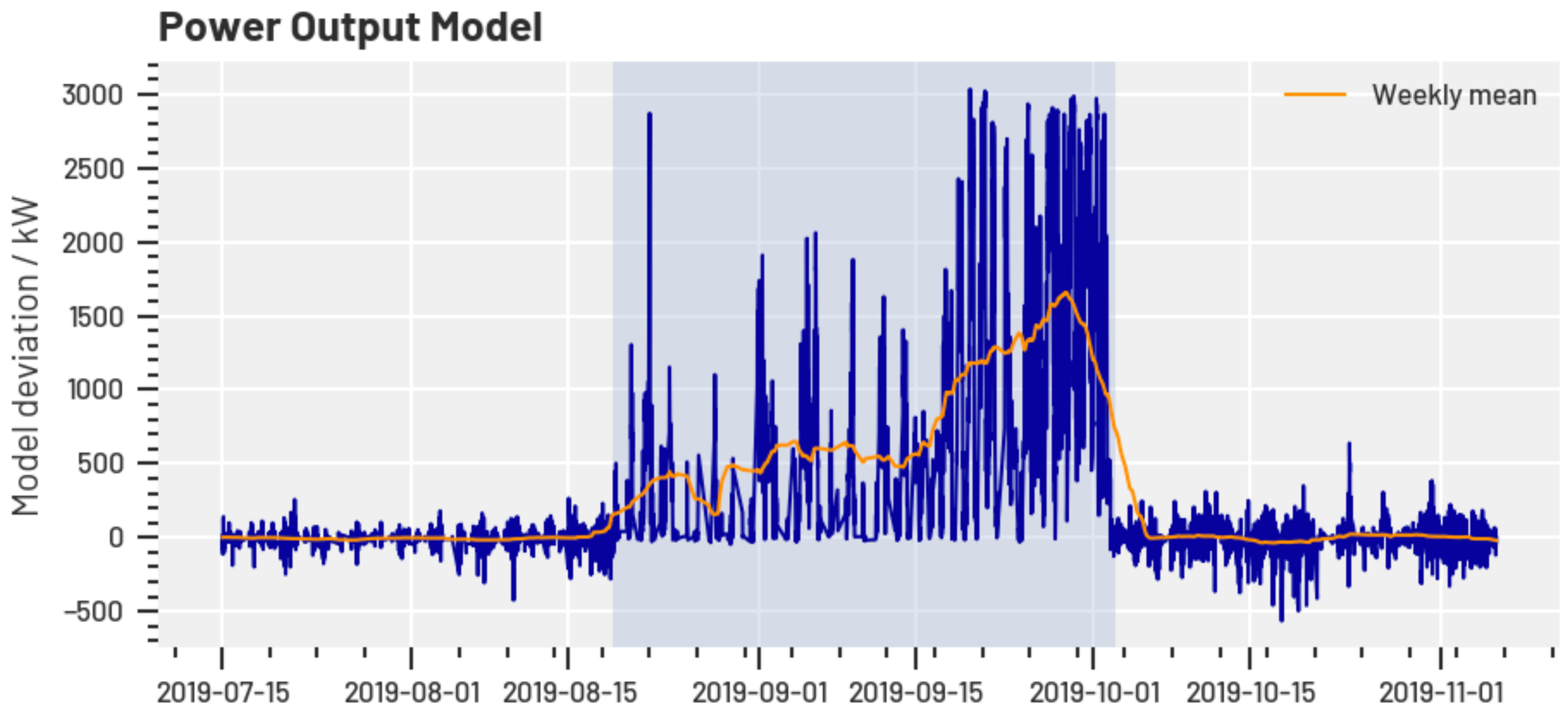
- Individual signals are affected by heterogeneity of units
- One signal on one unit may have a very different characteristic than on another
  - Slight differences in installation
  - Replacement
- A robust “signature” of a defect cannot be learned from this
- Alternative: individual anomaly detectors as feature space
- Only the combination of multiple detectors enables automatic diagnoses



Anomaly Space: Example

POWER OUTPUT MODEL

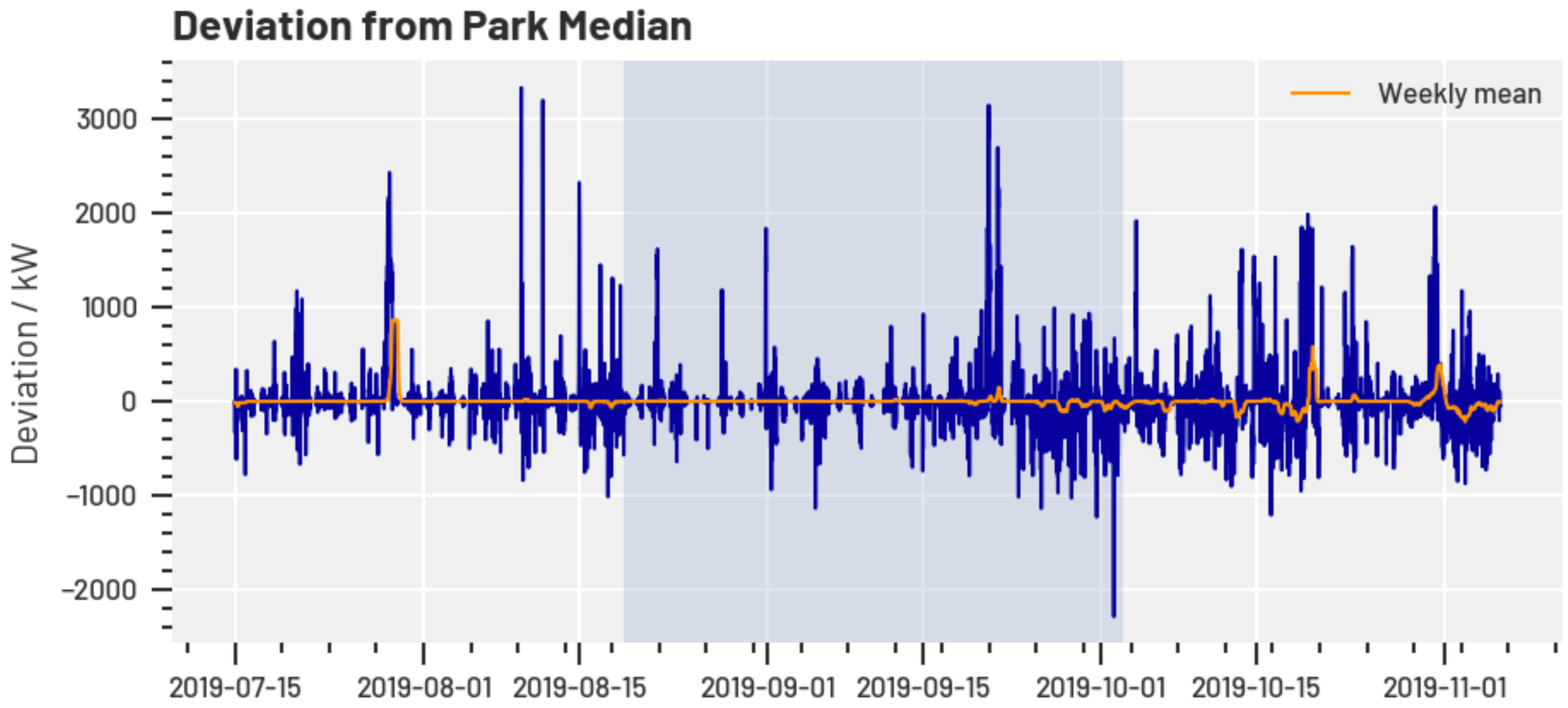
- Say we have a model that attempts to predict the power output of a wind turbine
- Inputs:
  - Wind speed
  - Ambient temperature
  - Nacelle azimuth direction
  - Wind direction
- This model now shows unusual deviations



Anomaly Space: Example

DEVIATION FROM PARK AVERAGE

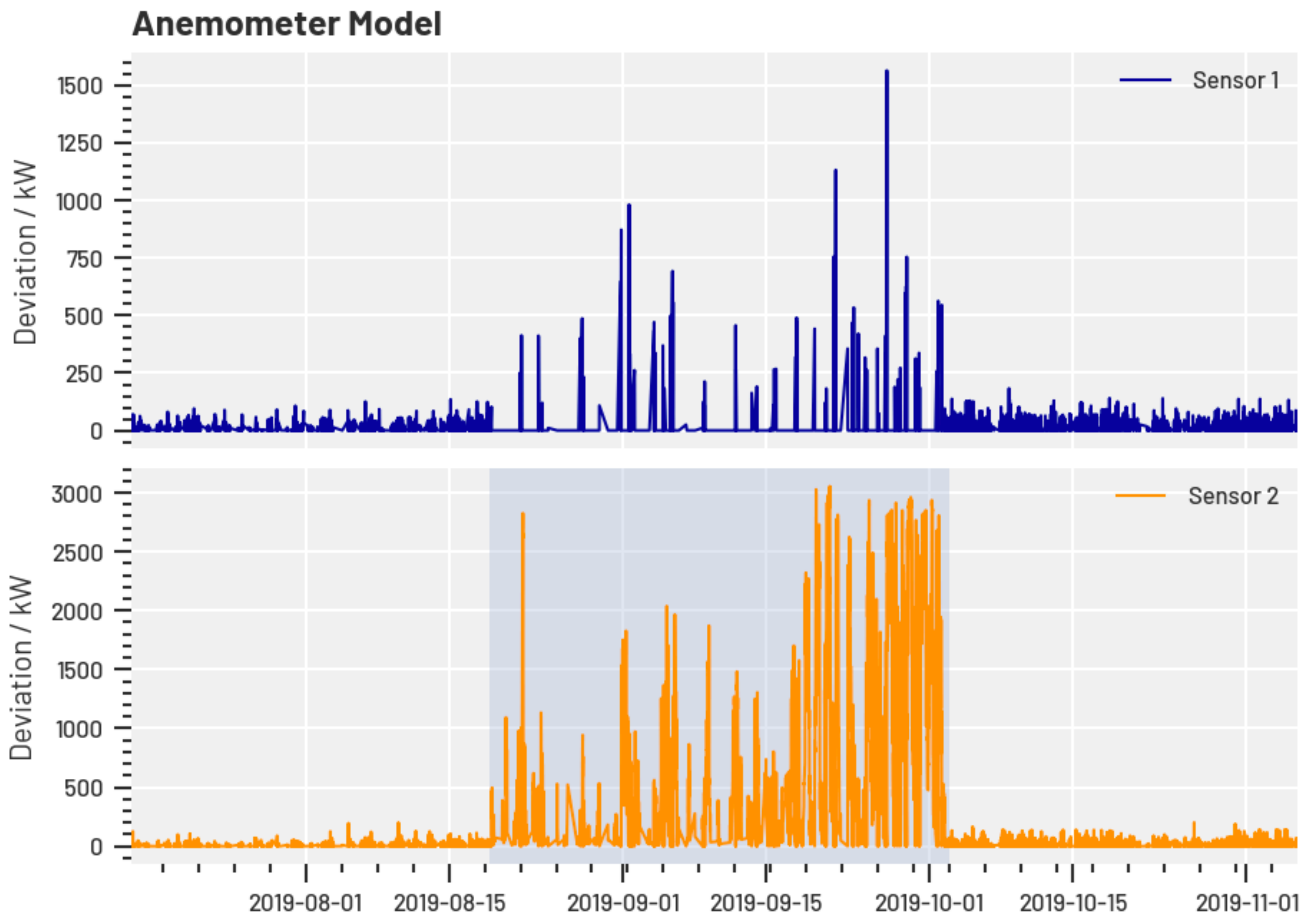
- Close-by units should exhibit comparable behavior
- However, no significant deviations visible



Anomaly Space: Example

COMPARING REDUNDANT SENSORS

- Anemometers are redundant at every wind turbine
- The wind turbine itself is actually a very reliable anemometer
- Comparing the three shows that one of them is actually defective



Takeaways

- Anomaly Detection of multiple time series poses a difficult problem
- Predictive Modeling is a way to monitor stability of multivariate relationships
- To ensure scalability, expert knowledge has to be used to train meta models
- Heterogeneity and lack of proper labels remain biggest challenges