

Discovery Through Situational Awareness

NASPI – Session 3: Data and Data Quality
March 2017

BRETT AMIDAN
JIM FOLLUM
CARLOS ORTIZ MARRERO

Pacific Northwest National Laboratory

March 29, 2017

DOE GMLC Award – Discovery Through Situational Awareness

► Project Goal

Create a tool that applies **statistical and machine-learning algorithms** in context of big data analytics to **investigate and implement anomaly and event detection** algorithms in near real-time

► Current Focus

- Working with the Eastern Interconnect
- Initial focus on phase angle pair analyses
- Provide the EI partners with a frequent (i.e. daily or weekly) report of the findings

► EATT (Engineering Analysis Task Team) White Paper

Data Mining Techniques and Tools for Synchrophasor Data

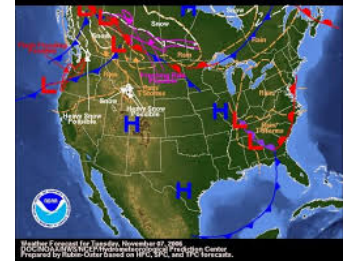
A high level view of data mining –

- What it is
- Why it is important
- How it -
 - 1) has been used in other industries,
 - 2) has been used in the power industry, and
 - 3) may be used in the future

“Big Picture” Vision



Power grid related
data (PMUs, State
Estimators, SCADA,
etc)



Other data (i.e.
weather [actual
and forecasts],
social media)

Data Driven Analytical Tool that provides:

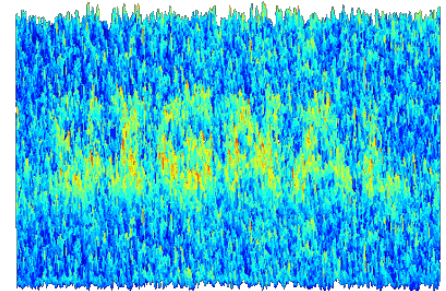
- Real time analytics, monitoring the state of the grid
- Capability to look at historical trends and events
- Reliable predictions about the forthcoming state of the grid

Is More Data Really Better?

Possibly, but beware of ...

- ▶ Data quality

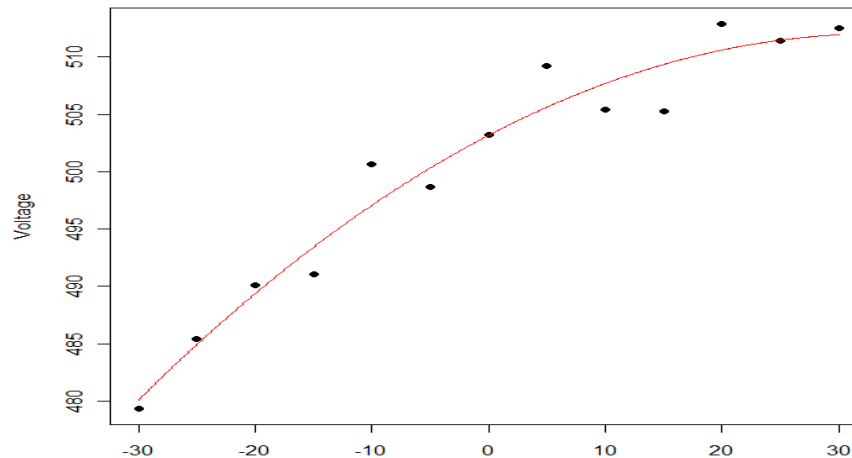
Poor quality data will drive your analyses



- ▶ Creating more noise, so that the signal is tougher to find

Feature extraction and feature selection are important steps that can really make a difference in the success of your algorithms

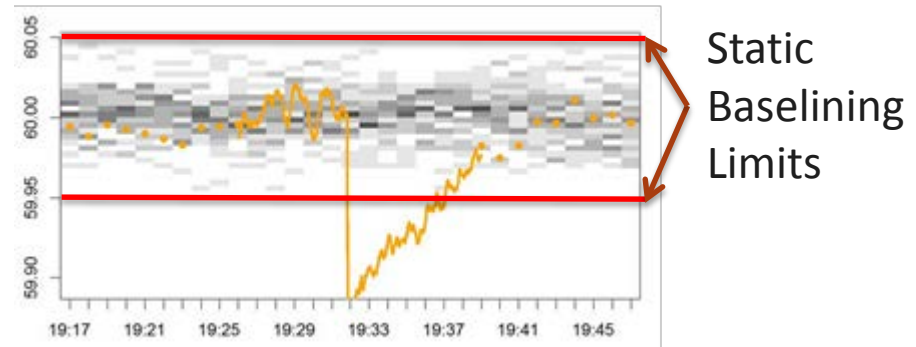
Feature Extraction (Data Signatures)



- ▶ Regression fits through the data calculate estimates of **value**, **slope**, **curvature** (acceleration), and **noise**.
- ▶ Can be calculated in the presence of missing or data quality flagged values.
- ▶ Summaries of these features are used in the analyses.

► Univariate Approach

- Create a baseline of typical behavior for each individual variable
- Determine abnormal behavior based on the baseline



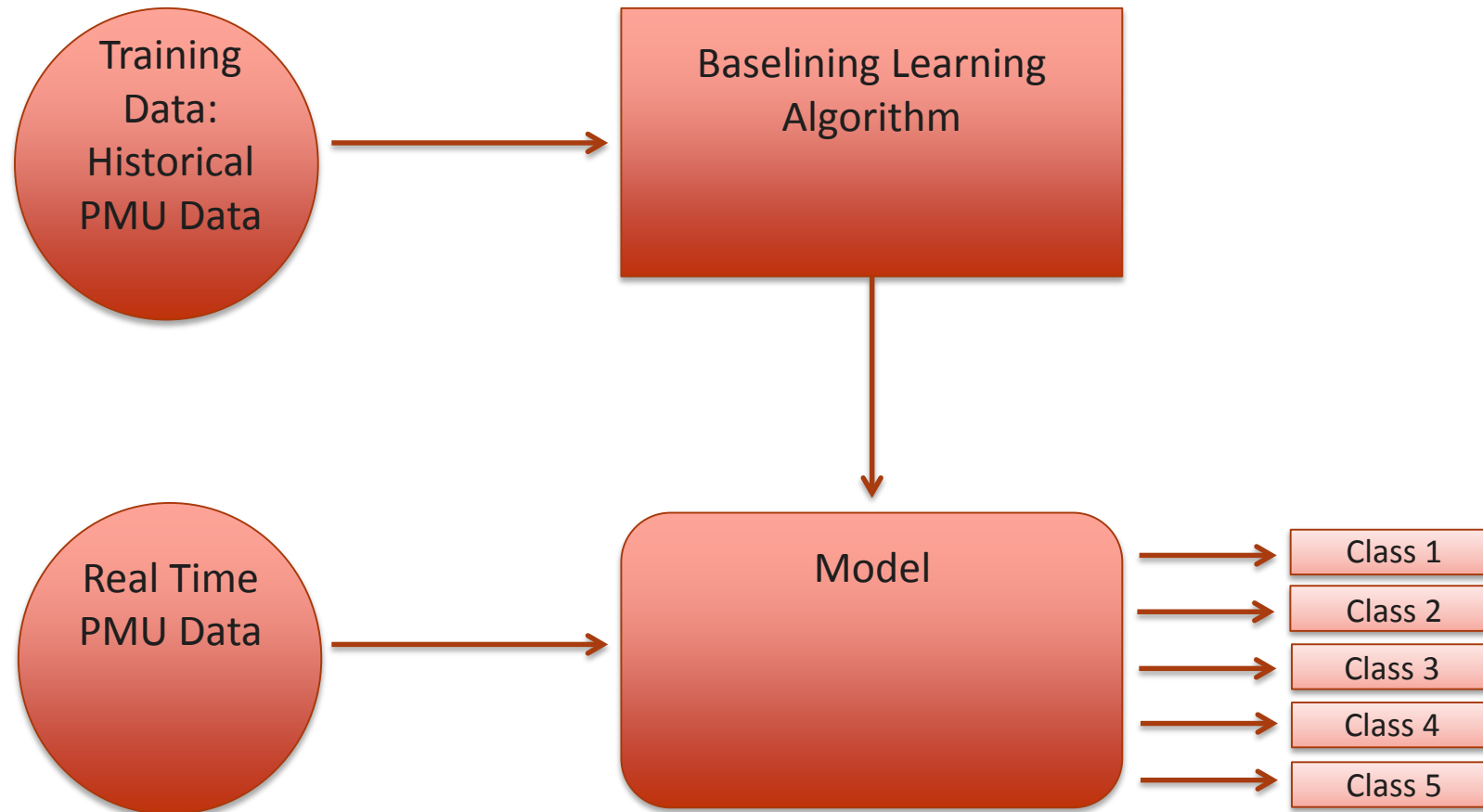
► Multivariate Approach

- Create a baseline across many (hundreds or even thousands) of variables
- Relationship between variables is considered when determining abnormal behavior

Baseline captures what normal behavior is expected to be

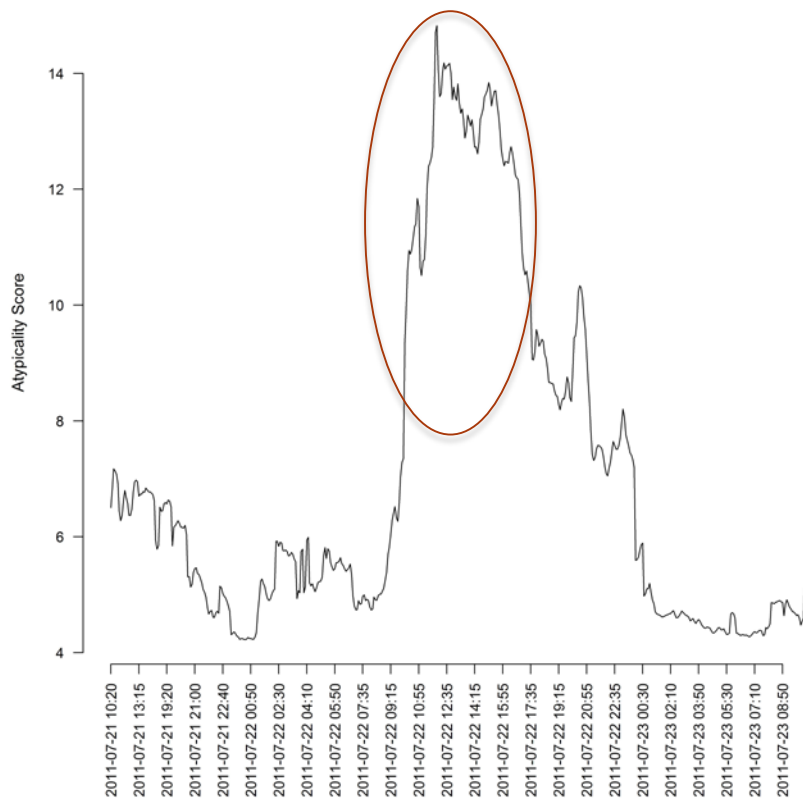
- ▶ Group similar behavior
 - **Time periods** that group together indicate normal grid behavior
 - **Variables** that group together indicate highly correlated variables and may be candidates for feature reduction
- ▶ Identify data that does not belong with the normal behavior
 - **Time period** contains data that is **unusual** (possible abnormal grid behavior)
 - **Variable** is unlike other variables, or something has happened to indicate a **behavioral change in the variable**

Creating a Baseline – Unsupervised Learning



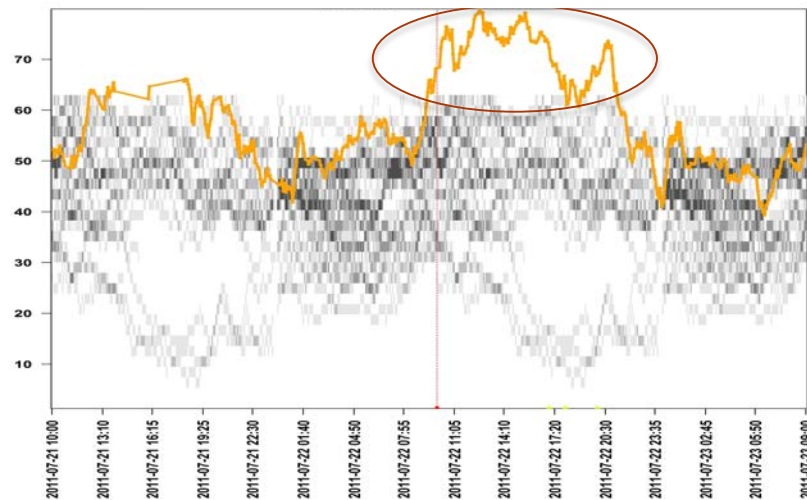
Identifying Data Driven Atypical Events

Using **multivariate** statistical techniques to establish baselines of typical behavior, atypical moments in time can be discovered and the responsible variables can be identified.

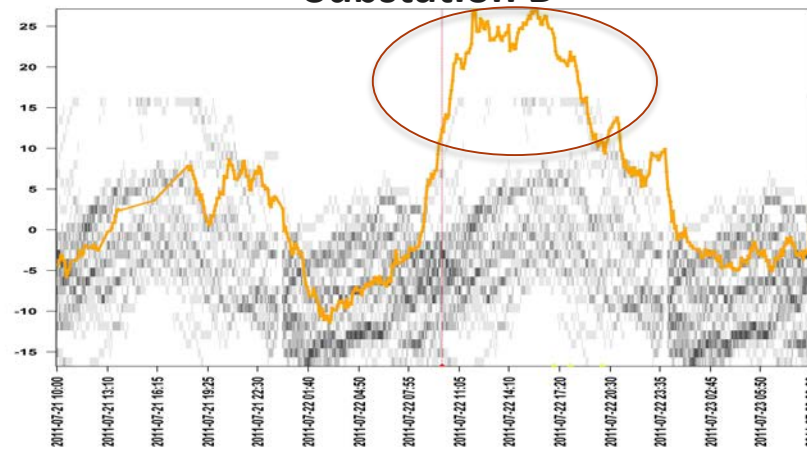


March 29, 2017

Substation A

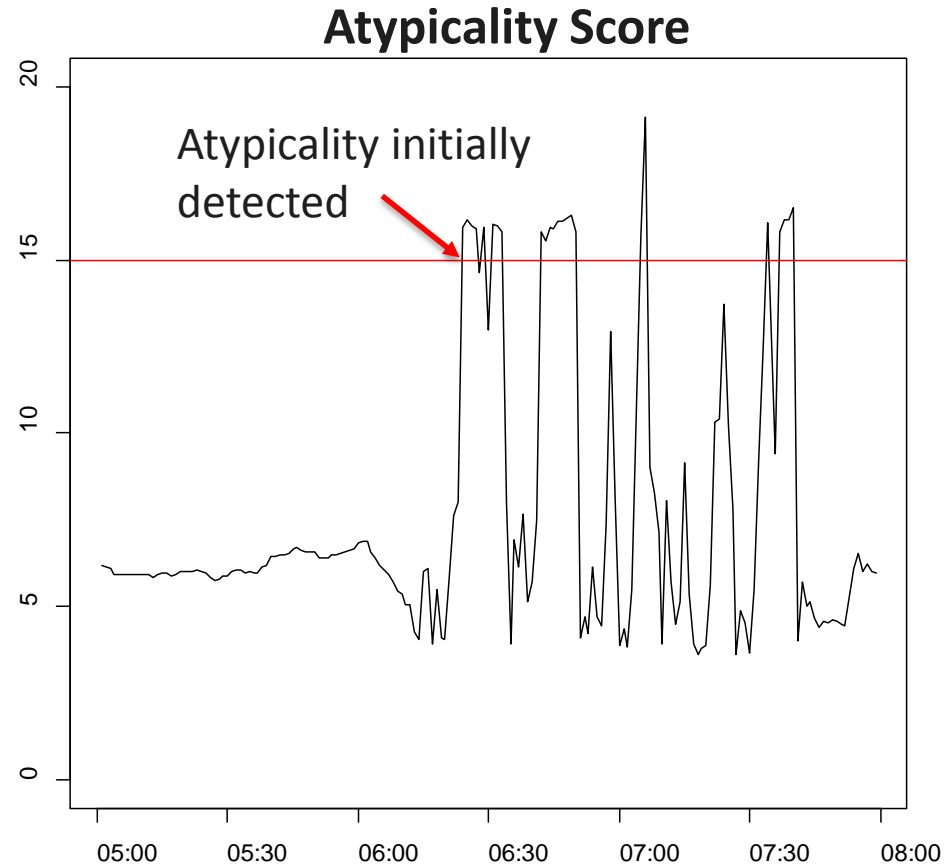


Substation B



Recent Atypicality Example

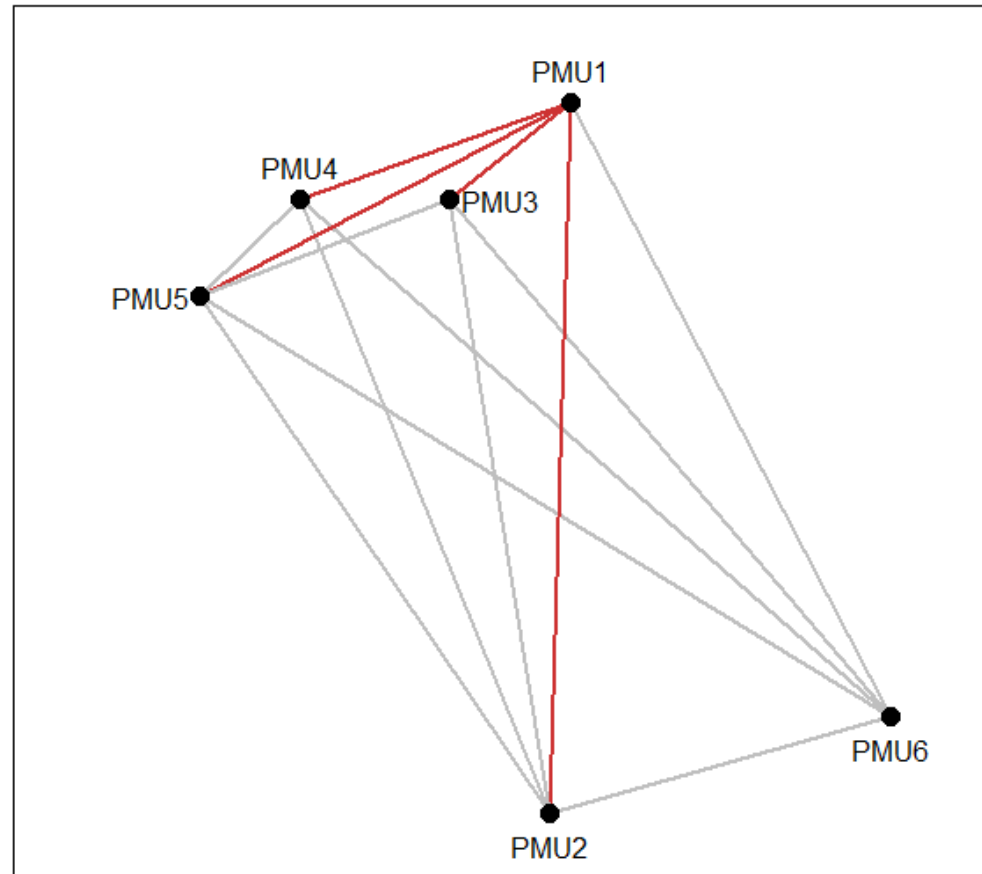
- ▶ Processed 5 months of 60 frames/sec PMU data (15 PMUs)
- ▶ This analysis only focused on phase angle pairs
- ▶ Atypicality first detected at 6:23 and then atypicality occurred off and on for the next hour or so.



All results have been de-identified

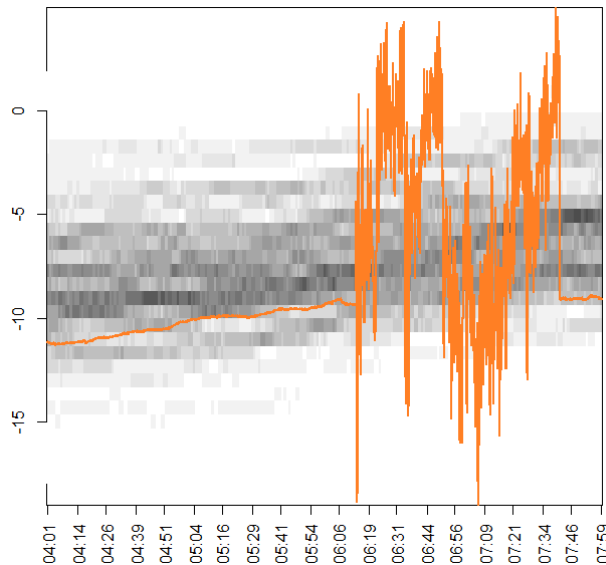
Atypicality Displays

- Spatial plot showing which phase angle pairs were contributing to the atypicality (red indicates atypical)

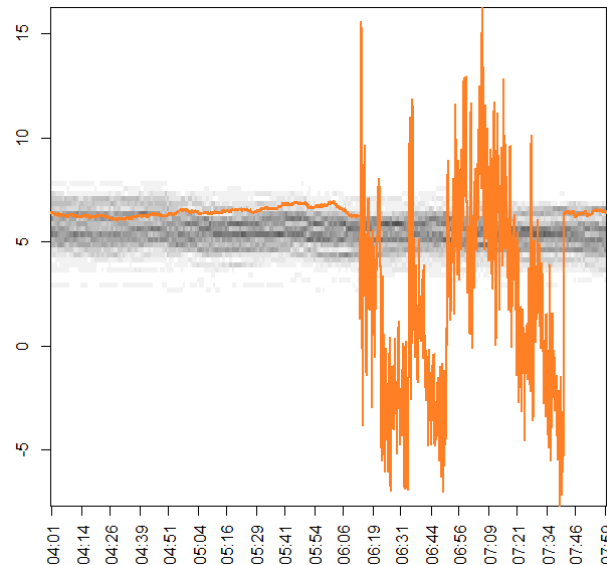


Atypicality Displays

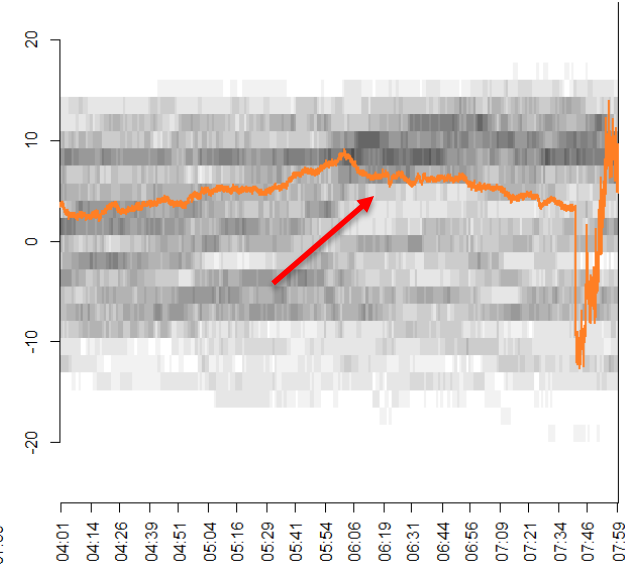
PMU1-PMU2 Pair



PMU1-PMU3 Pair



PMU1-PMU6 Pair

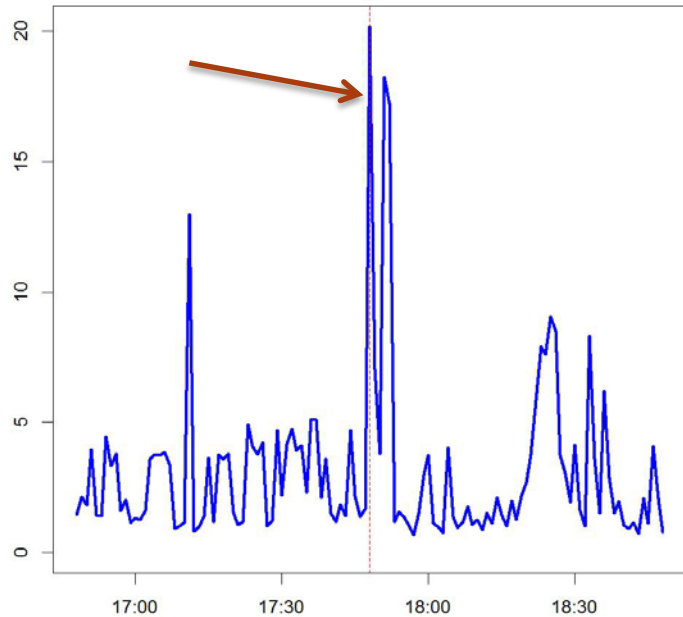


2 of the 4 angle pairs that were significant.

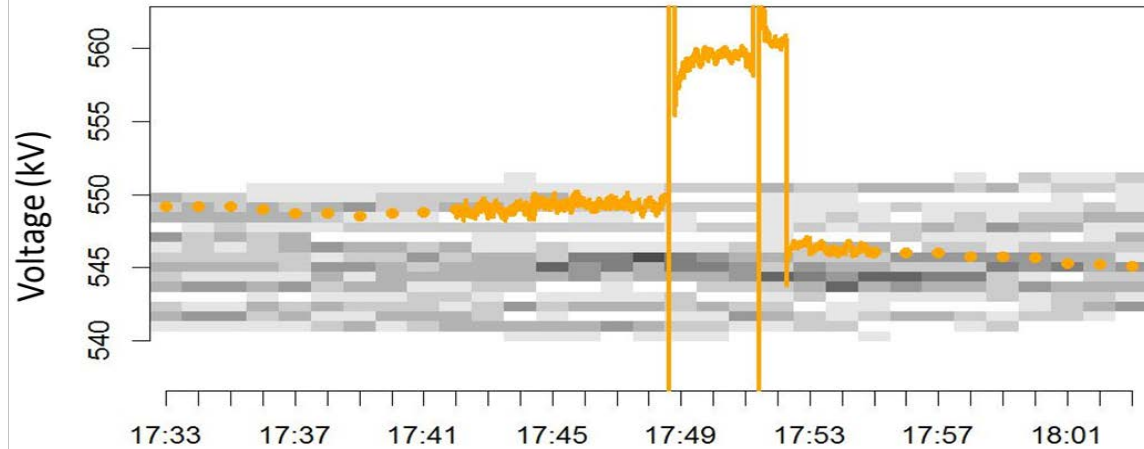
Angle pair was not significant, although it also contained PMU1.

Atypicality Detection Lightning Related Anomaly

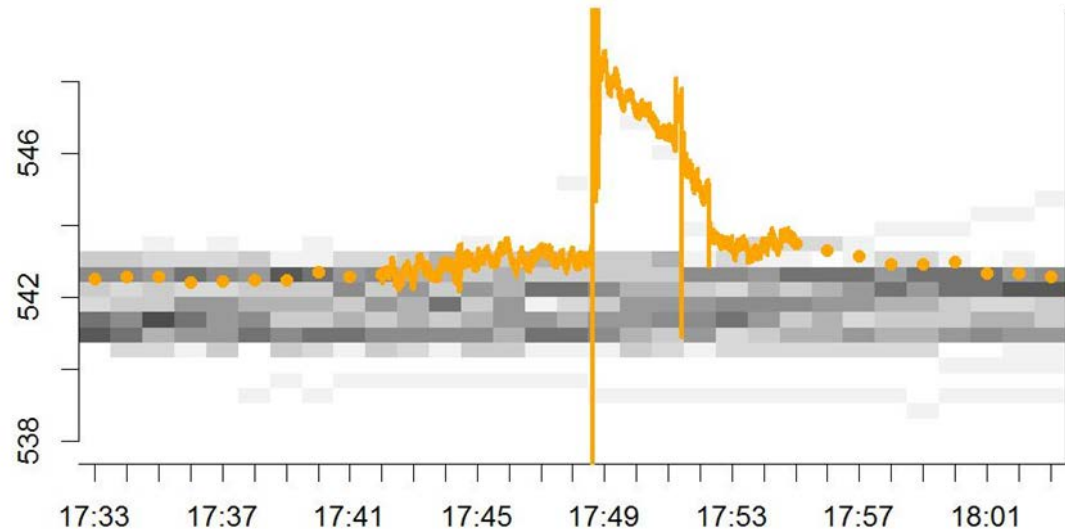
Atypicality Score



Substation A

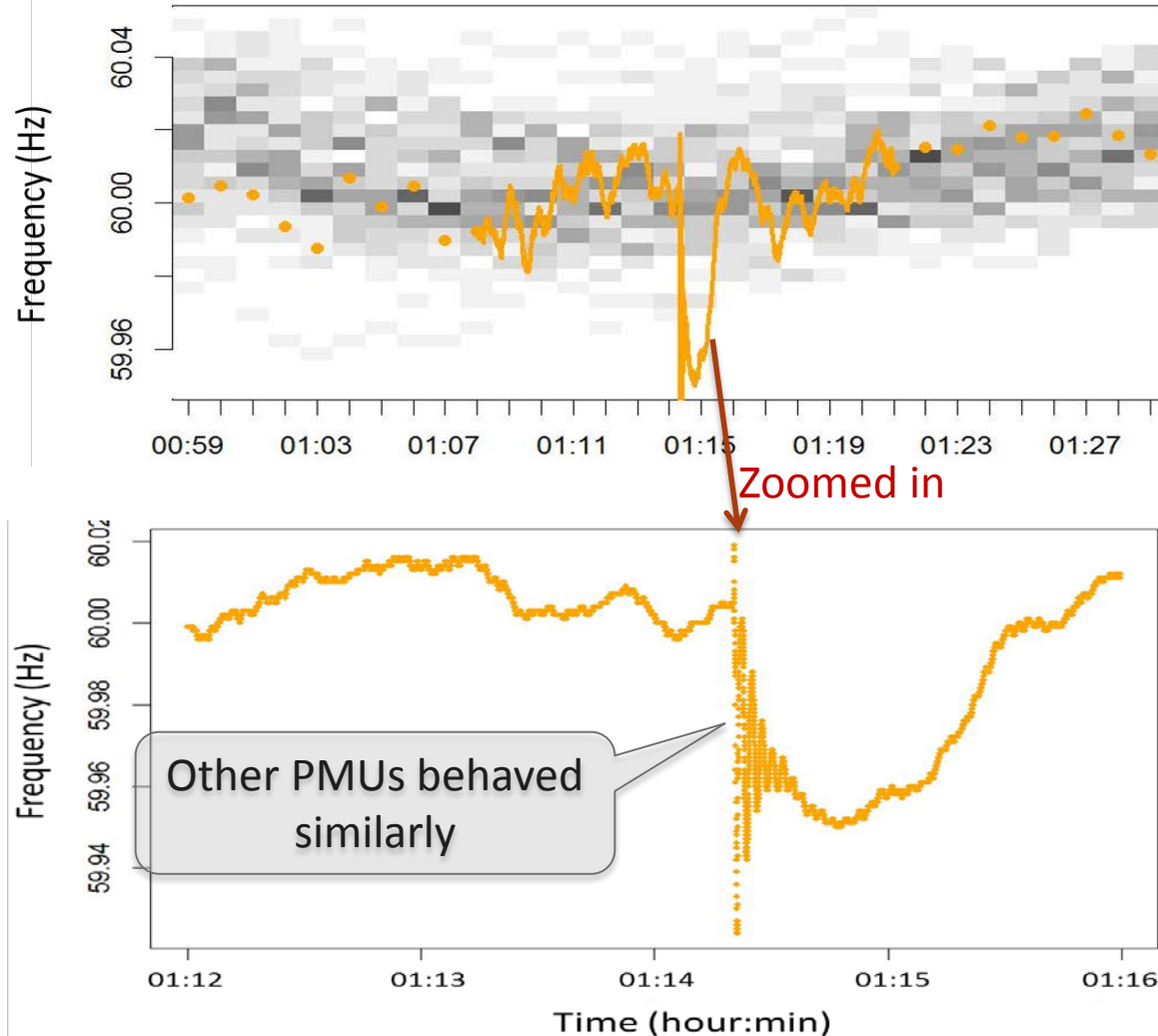
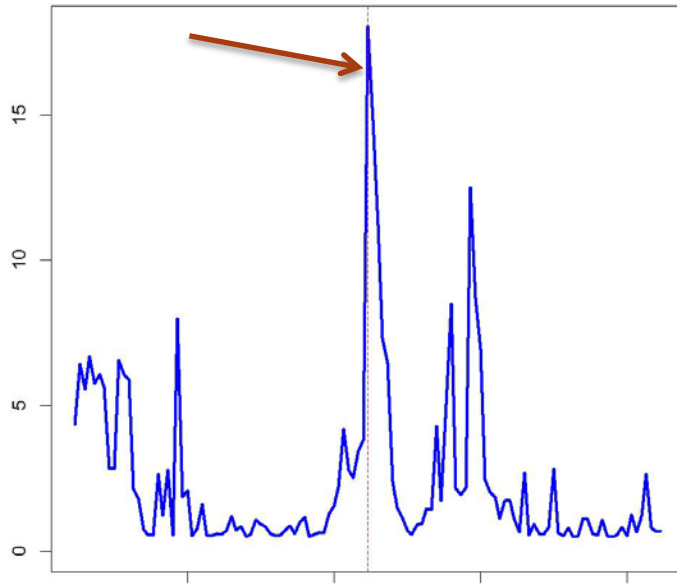


Substation B



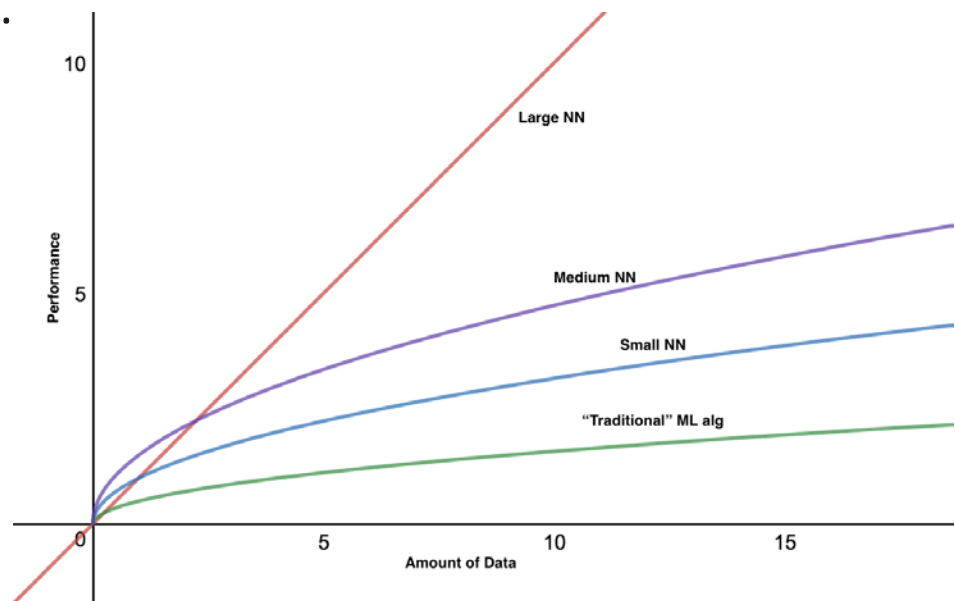
Atypicality Detection Anomaly Related to Loss of Generation

Atypicality Score



Unsupervised Learning Neural Networks

- **What** are neural networks?
 - Machine learning models that can learn highly non-linear behavior.
- **Why** we need neural networks?
 - For sufficiently large networks, performance becomes a function of the amount of data.



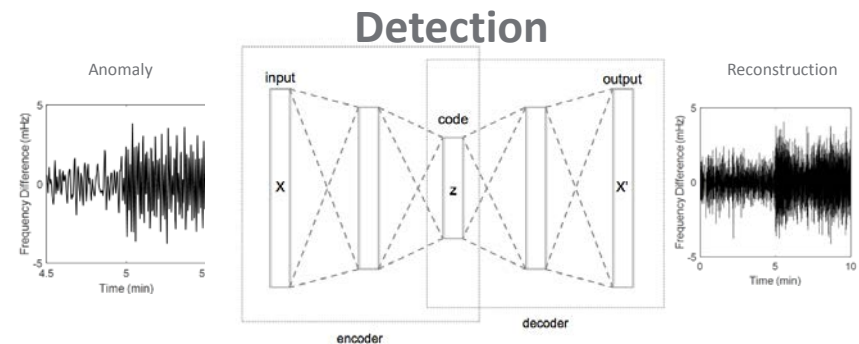
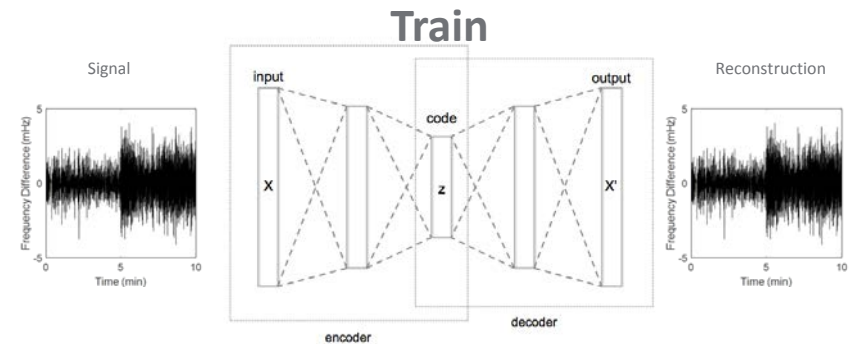
Neural Networks for Power Grid Data

- Neural networks a perfect fit for **power grid** applications because:

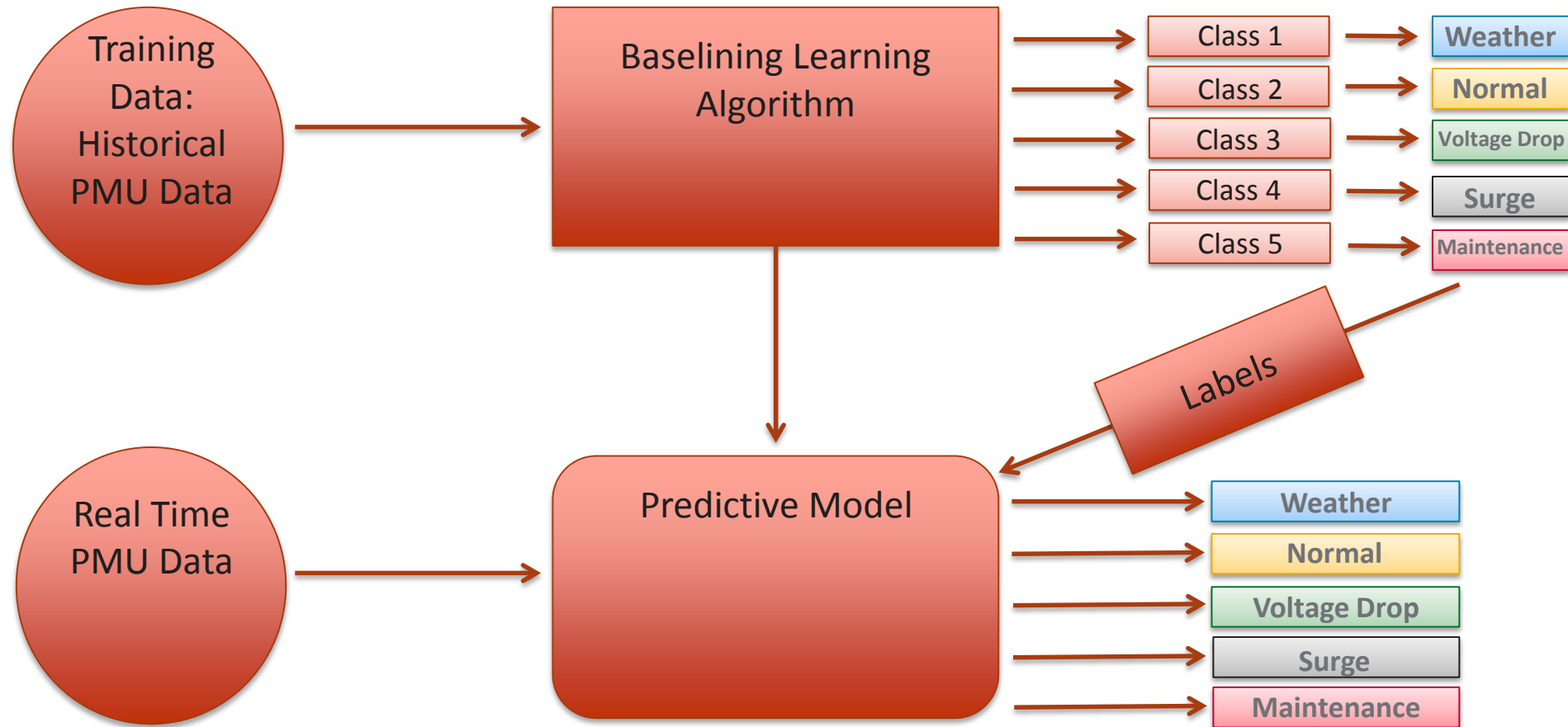
- We have access to a lot of data (volume, high frequency).
- Power grid behavior is highly non-linear.

Example: Detecting Oscillations in Power System

- Oscillation events are rare and can be difficult to detect.
- **Approach:** Train a neural network (called **autoencoder**) to learn when the grid is stable.



Supervised Learning



Conclusions

- ▶ The power grid community is in the infancy stages of applying statistical and machine learning algorithms.
- ▶ Care must be taken in determining which data should be used, how features can be extracted from the data, and selecting which features will provide insight.
- ▶ Initial results show that data driven anomalies can be identified using multivariate analyses techniques. Some of these anomalies correspond to actual events, but some do not.
- ▶ The potential is great in bringing valuable insight into the power grid community by applying multivariate statistics and machine learning techniques.