



Deep Learning Application for Power Grid Event Detection and Classification

April 25, 2019

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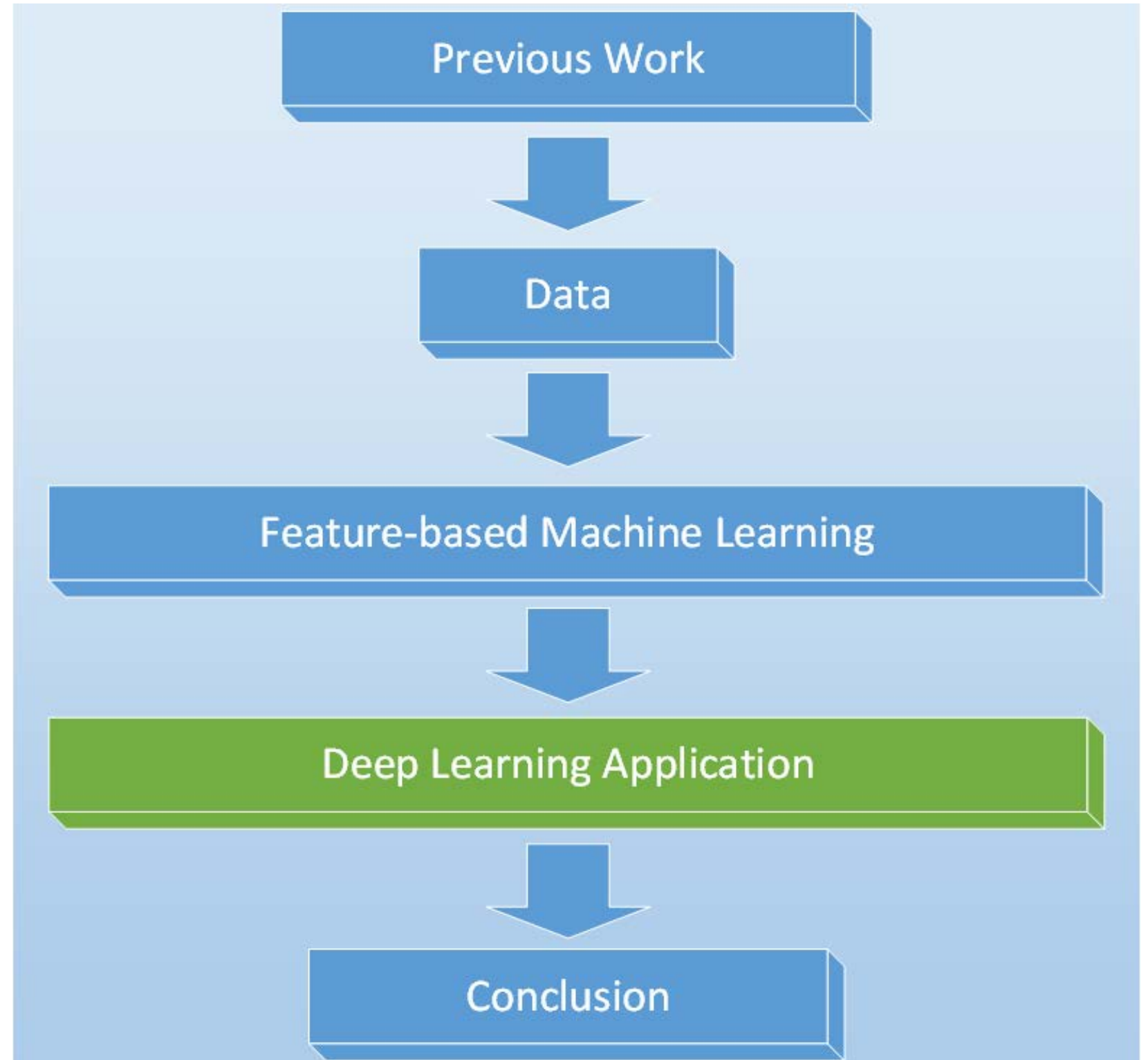


PNNL is operated by Battelle for the U.S. Department of Energy

PNNL-SA-140555



Outline



PNNL Big Data Pathway



Aircraft safety
Morning Report
w/ NASA



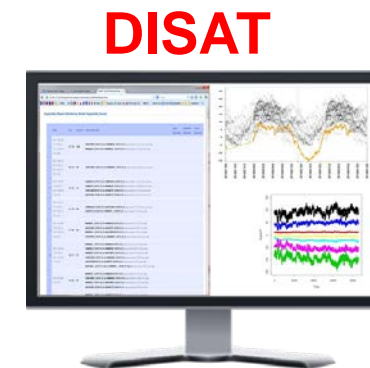
Analytics Using
State Estimator
Data
w/ EI



Data
Investigations
Using PMU Data
(uncovering data
quality issues,
etc.)



GMLC, ESAMS, and Beyond
Machine learning basis
Many additional data streams
Predictive analytics



DISAT

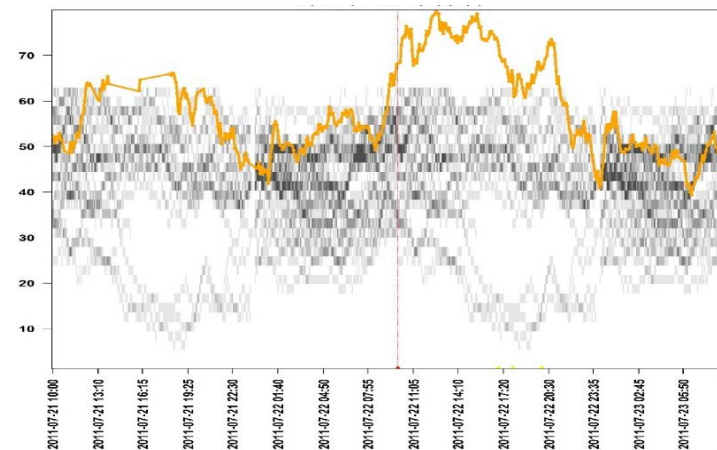
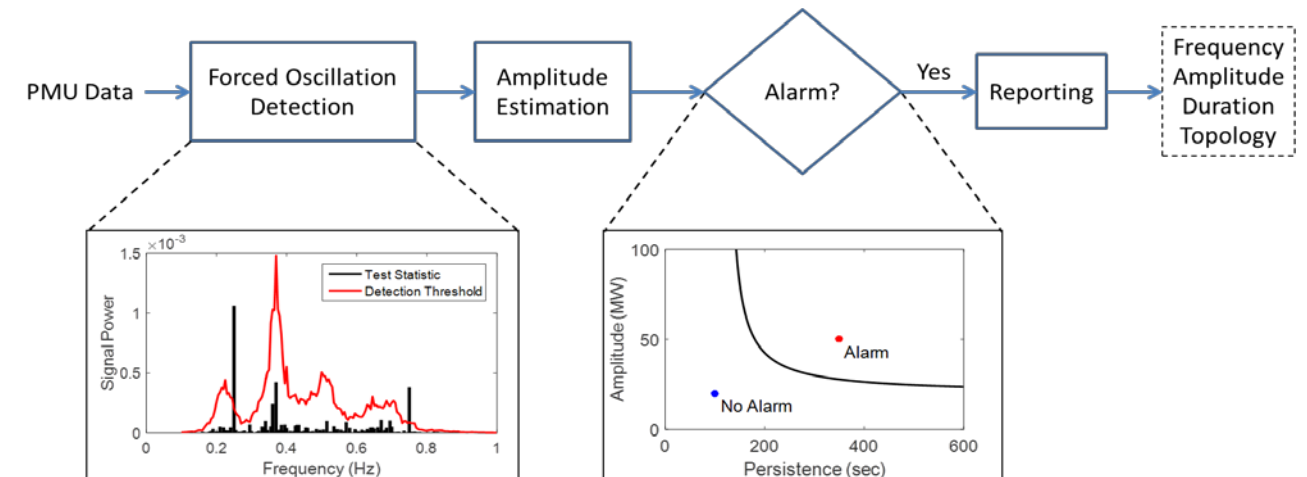
Data **I**ntegrity
Situational
Awareness **T**ool
(PMU Data
Analytics w/ BPA)

ESAMS – Eastern Interconnect Situational Awareness Monitoring System

Project Objective:

To introduce a common, high-level interconnection-wide view based on synchrophasor information

- Detect and identify forced and natural oscillations
- Monitor wide area phase angle pairs and identify when values are outside of normal ranges
- Detect current atypical behavior based upon baselining previous behavior
- Recently installed at PJM

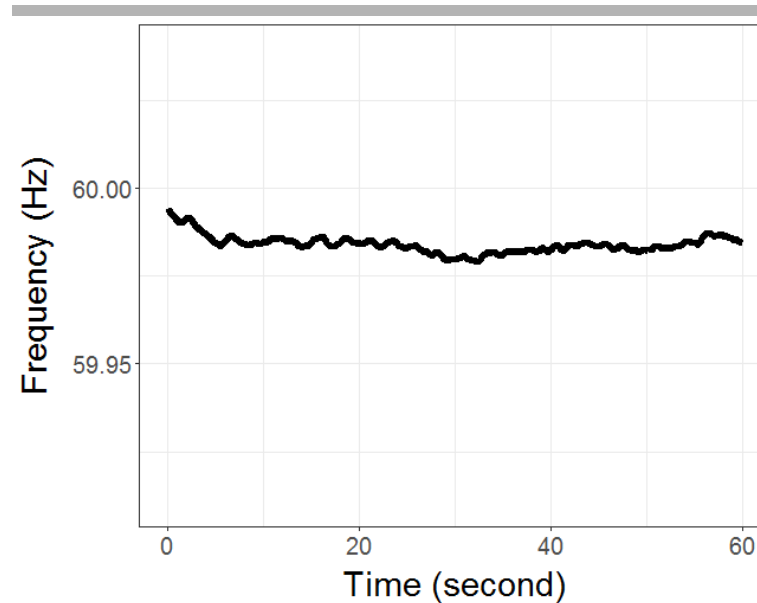


Research Questions

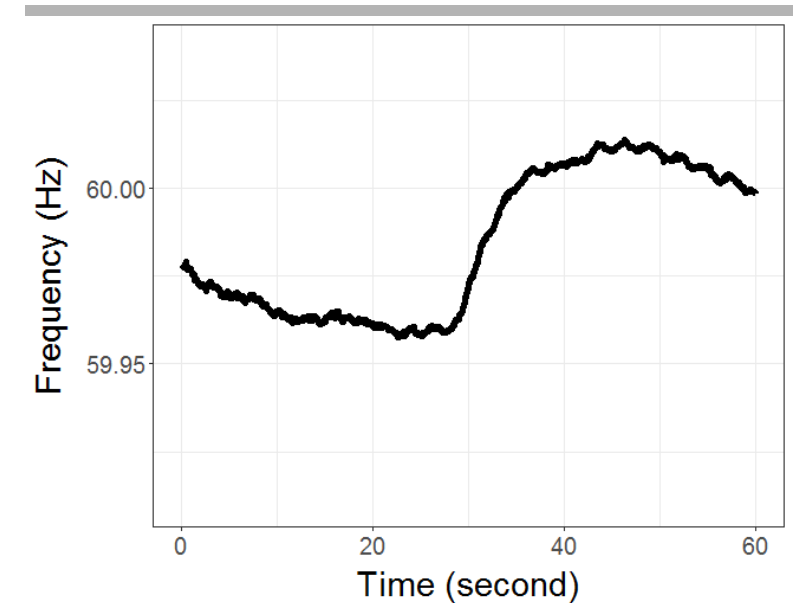
- Will deep learning be useful for PMU data analytics?
 - Since it has been successful in so many areas...
- Which deep learning technique and how to implement?
 - Convolutional neural network (CNN) vs. Recurrent neural network (RNN) (Long short-term memory (LSTM))
 - What kind of data preprocessing do we need for PMU data to be used by deep learning?
- What are the advantages and disadvantages of deep learning compared to traditional feature-based time series machine learning for PMU data?

PMU Data

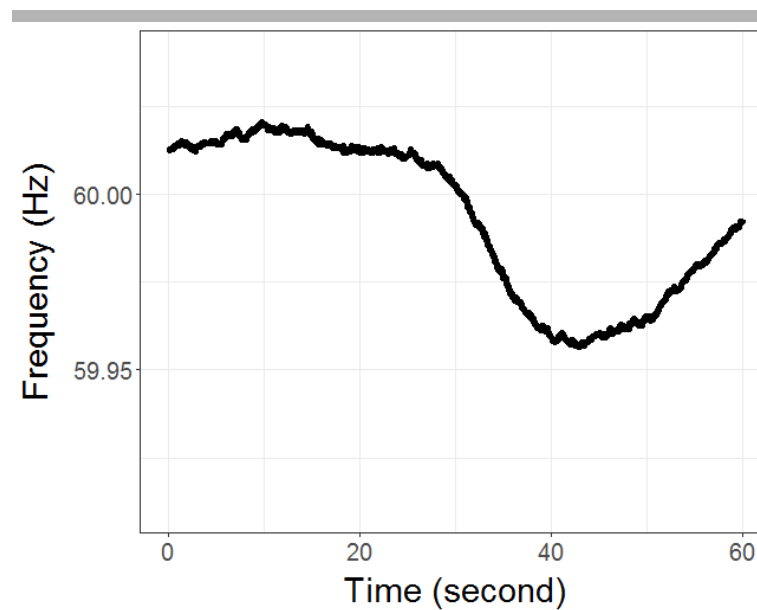
- Obtained from Western Interconnect;
- 2016 to present;
- 12 PMUs;
- Hundreds of events.



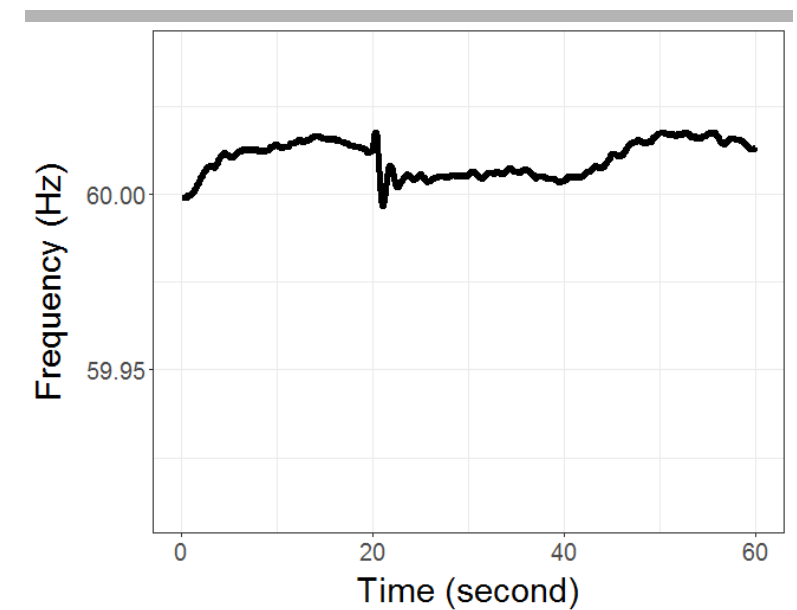
Normal Minute



Event Type A

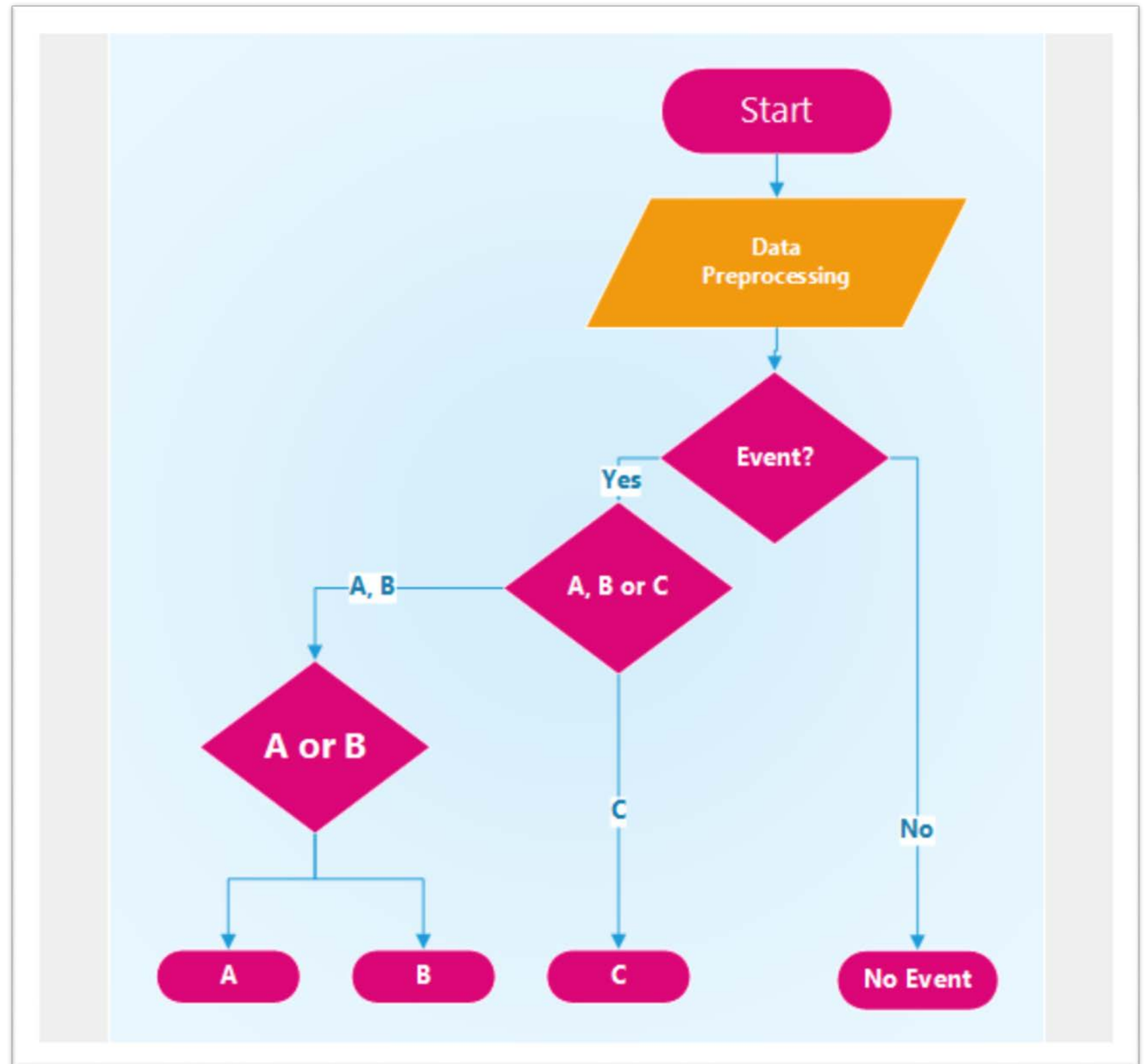


Event Type B



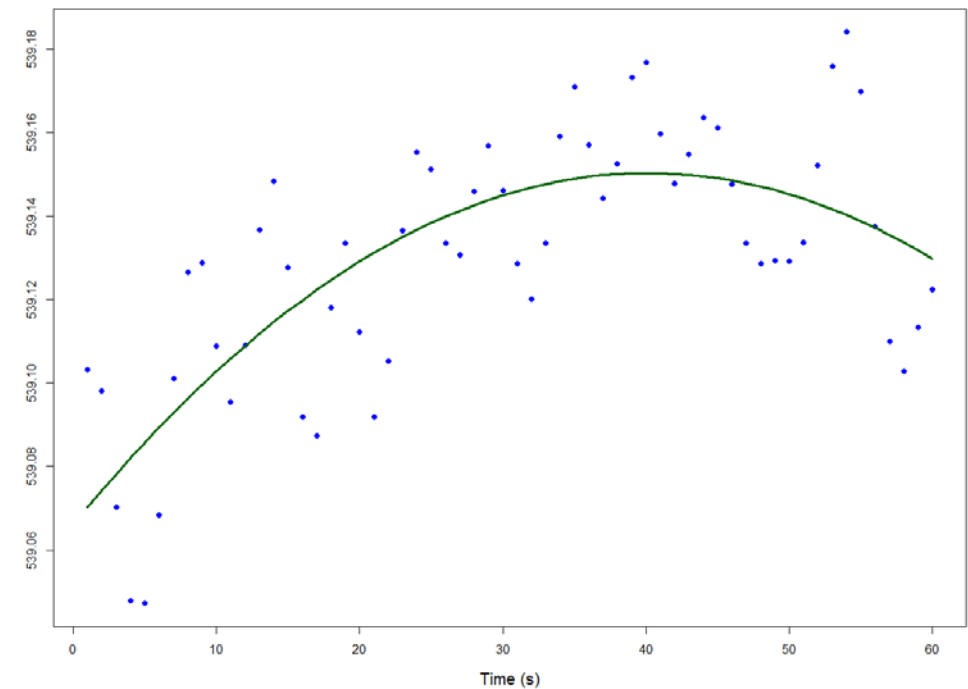
Event Type C

Event Detection and Classification Steps



Feature-based Machine Learning

- Feature extraction: “16 signature elements” (Amidan and Ferryman 2005).
- The goal is to capture the essential information of a time series while reducing dimensionality.
- Quadratic Regression: $y = a + b x + c x^2 + \epsilon$
 - Maximum,
 - mean,
 - minimum,
 - and standard deviation of a , b , c , ϵ .



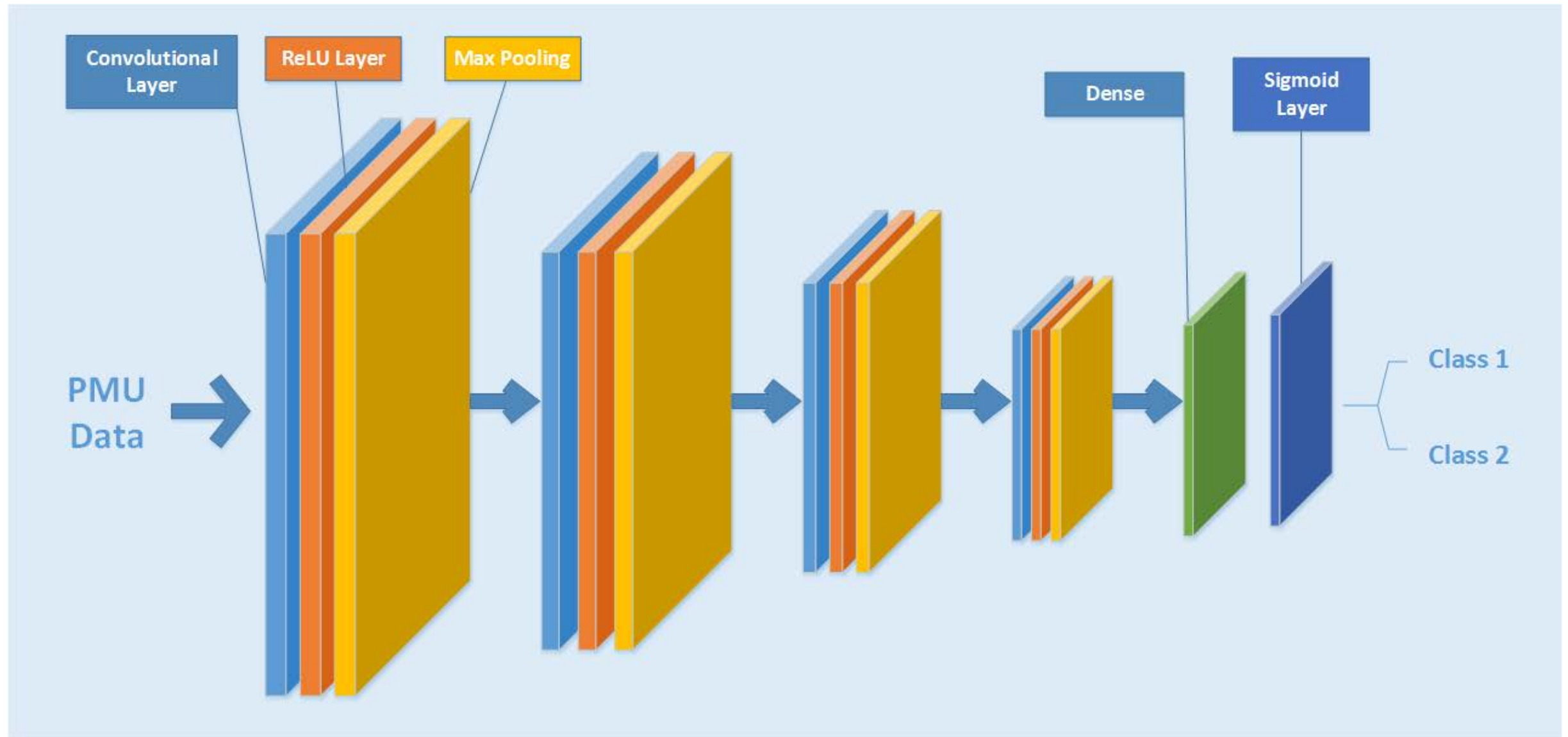
Feature-based Machine Learning

- Gradient boosting machine (GBM).
- Relies on the extracted features as inputs.
- An ensemble of weak learners to form a stronger learner.
- Weak learners are typically decision trees.
- Fitting on residuals of previous learners.

Deep Learning: CNN vs LSTM

- Convolutional neural network (CNN) vs. Long short-term memory (LSTM)
- Theoretically, LSTM fits time series data better since it focuses on temporal correlation;
- However, practically, CNN works better for PMU data!
- PMU data has high sampling rate;
- 1-dimensional CNN is very good at capturing patterns (shapes) of PMU data.

Convolutional Neural Network Model in this Study



Convolutional Layer

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

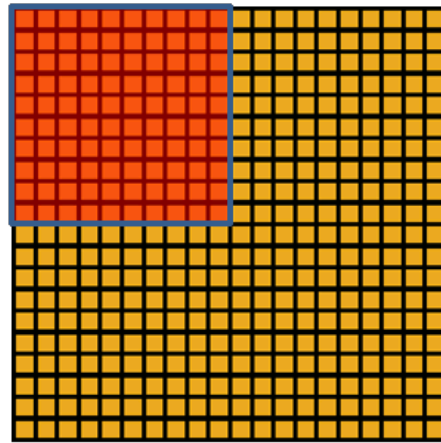
Image

4		

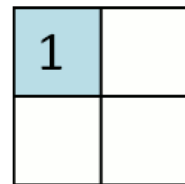
Convolved
Feature

- Filters (or kernels) stride through the data to create feature mapping;
- Detects specific features at some spatial (or temporal) position in the data;
- Automatic feature generation.

Max Pooling



Convolved
feature



Pooled
feature

- A form of down-sampling;
- The exact location of a feature is not very important;
- Reduce overfitting;
- Deeper layers learn bigger picture.

Results (10-fold cross validation)

	CNN (Deep Learning)	GBM (Machine Learning)
Step 1 (Normal vs. Events)	95.5% ± 2.8%	95.0% ± 2.5%
Step 2 (A, B vs. C)	96.2% ± 2.0%	96.5% ± 2.0%
Step 3 (A vs. B)	97.4% ± 2.3%	96.6% ± 1.7%

1. Results are overall accuracy. Sensitivity and specificity are quite similar.
2. Results are based on 487 events from over 1 year of PMU data.

Deep Learning Conclusions

- **Deep learning provides automatic feature extraction, while machine learning needs features to be already engineered and extracted;**
- Deep learning is more complicated to implement with various structure options and more hyper-parameter tuning;
- Deep learning is more difficult to converge, have to try different optimizers and learning rates;
- However, deep learning has a greater potential to fit more power grid applications because of its ability to adapt to unseen problems;
- Future work: focus on applying DL for multiple-channel PMU data.

Thank you

Questions?

