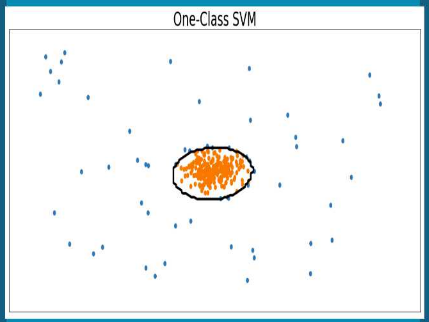
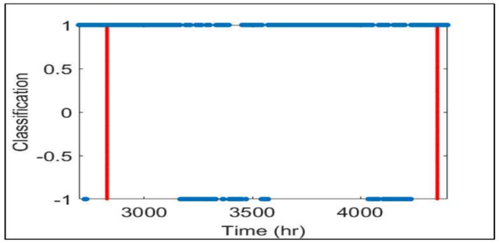
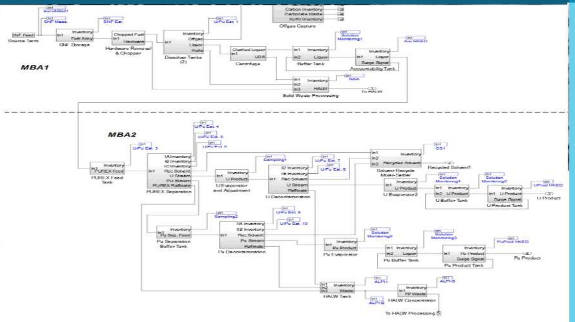
SAND2019-7404C

Unattended Monitoring and Machine Learning for Safeguarding a PUREX Reprocessing Facility







PRESENTED BY

Nathan Shoman and Benjamin Cipiti

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Outline

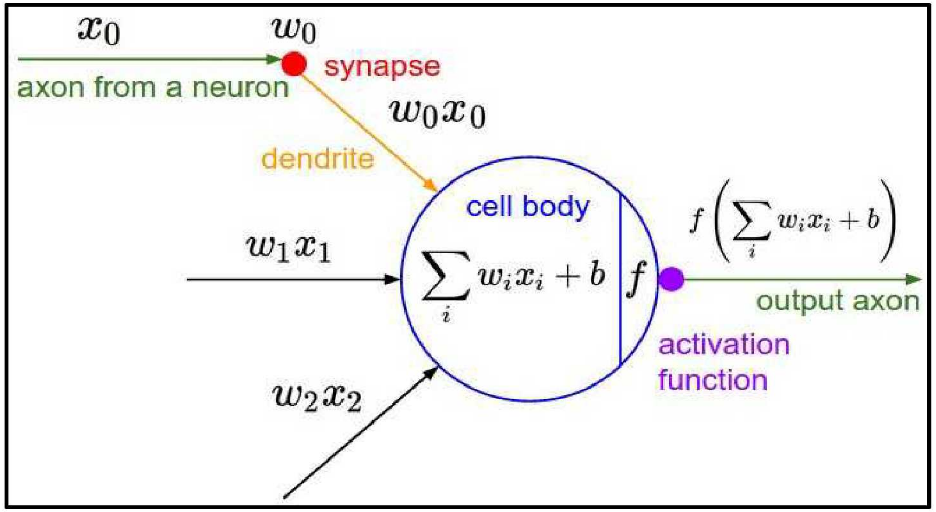
- Motivation
- Process model
- Machine Learning methods
  - Feedforward neural networks
  - Long-Short Term Memory (LSTM) neurons
  - One-Class Support Vector Machine (LSTM)
- Machine learning framework
- Initial results
- Conclusions and future work

Elimination of on-site laboratories at reprocessing facilities is a long-standing goal of the IAEA

- Currently on-site laboratories are required for large throughput bulk handling facilities under IAEA safeguards, such as PUREX reprocessing facilities
  - Require small measurement uncertainties to have an acceptable sigma MUF value
  - Expensive and time consuming
  - Can new approaches reduce the need for destructive analysis and consequently on-site laboratories
- Proposed machine learning framework uses non-destructive analysis (NDA) measurements to detect facility anomalies such as diversion or misuse
- Measurements could be left unattended outside routine calibration
- Framework is to aid the IAEA safeguards implementation, not to replace inspectors

Feedforward neural networks are powerful tools that can learn any continuous function

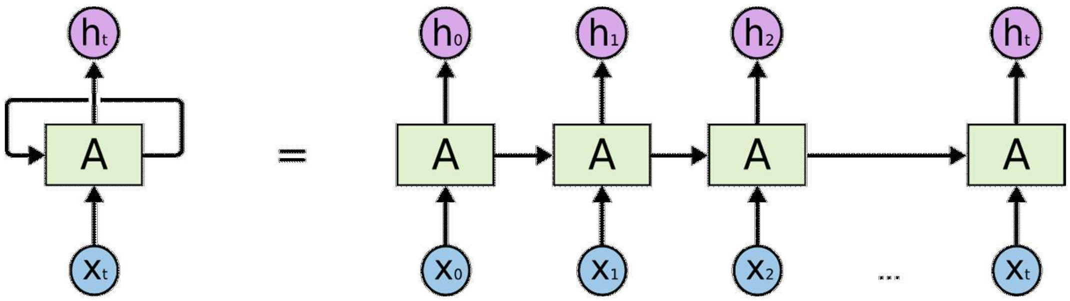
- Neurons receive signals, send output to connected neurons
- Activation functions allow for learning of non-linear functions
- Weights are adjusted during training to more closely match desired output
- Neurons are arranged in a network



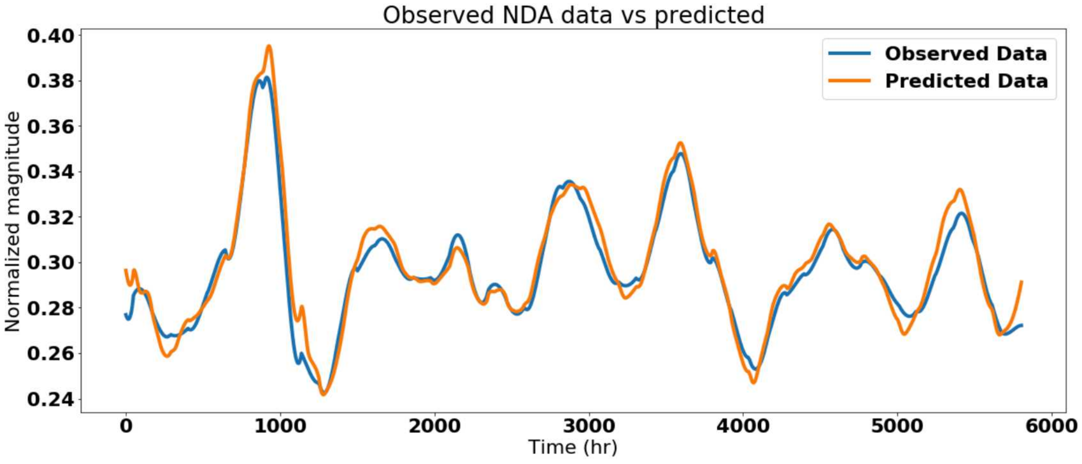
http://cs231n.github.io/neural-networks-1/#feedforward

Recurrent neural networks can address temporal dependencies in data

- Recurrent neural networks learn time-dependent behavior by passing information to other parts of the network
- Very effective in other areas of machine learning such as speech recognition or language translation
- Used to predict the next time-step of a NDA gamma signal in this work
- Gamma peaks from previous time are used to form a history. The history is used to predict the next step.
- Difference between predicted value and observed is the reconstruction error

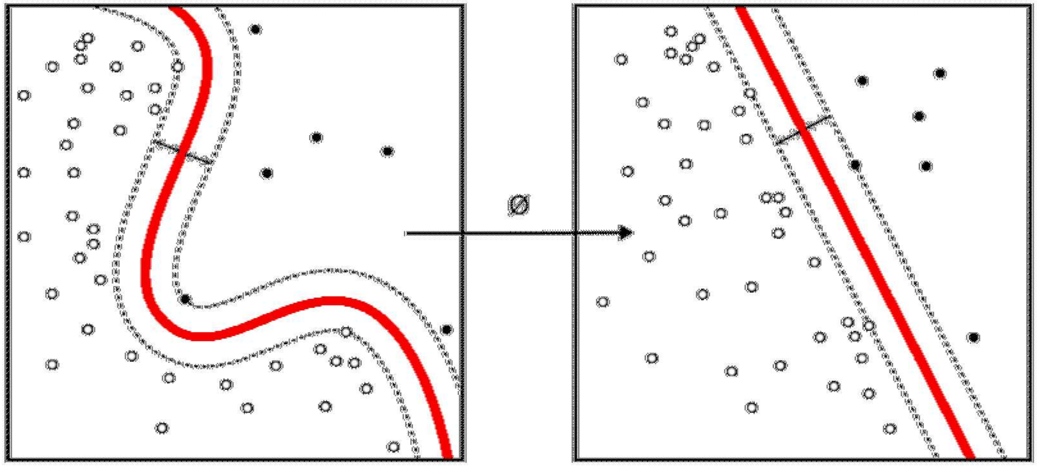


https://colah.github.io/posts/2015-08-Understanding-LSTMs/



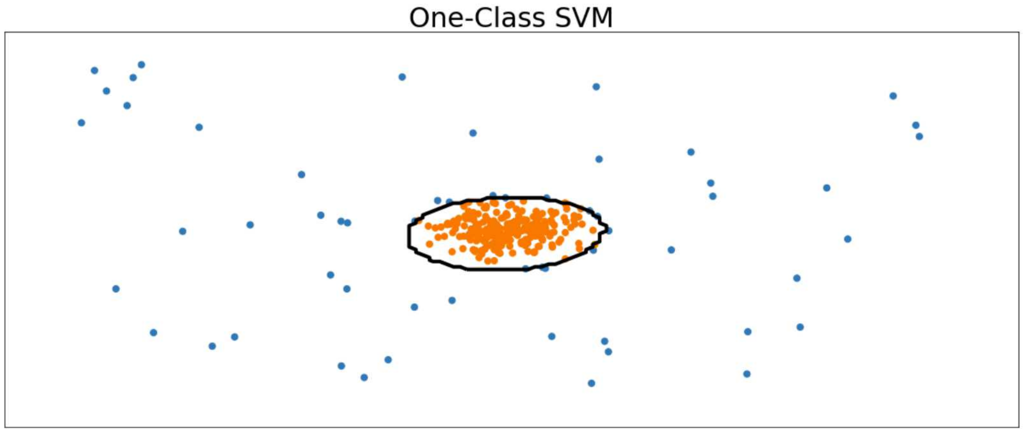
Support Vector Machines are powerful tools for classification tasks

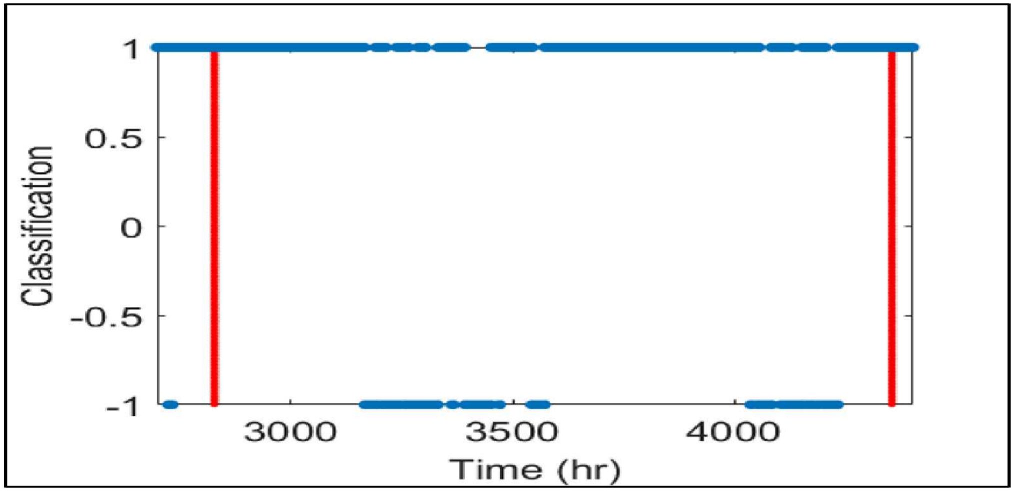
- Traditional Support Vector Machine (SVM) is a supervised method to calculate a classifier between to classes of data
- Large-margin classifier method that attempts to maximize the separation between classes
- Uses a hyperplane to separate data – however most datasets not linearly separable
- Kernel methods used to transform data into a higher space to separate data



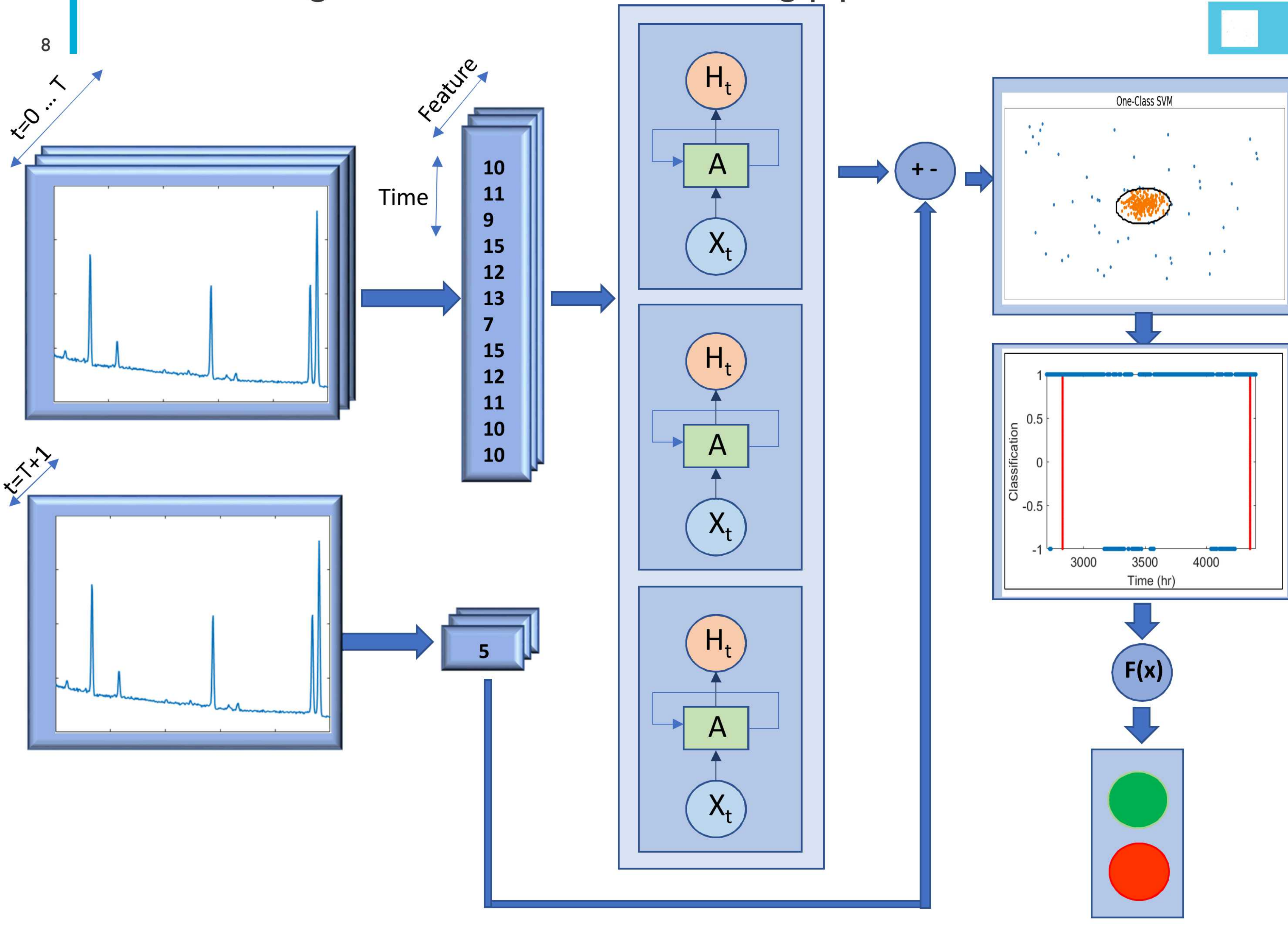
One-Class Support Vector Machines are an extension of the Support Vector Machine formulation

- SVM can be reformulated as an unsupervised classification problem
- SVM is trained to separate *p* from 1-*p* of the data where
  - $\varepsilon \leq p \leq (1 - \varepsilon)$
  - $\varepsilon \cong 10^{-10}$
- Controlling *p* adjusts sensitivity to off-normal conditions
- Under normal operation some observations are classified as off-normal, but density of outliers is low
- Density of outliers is used to determine false alarm probability and probability of detection





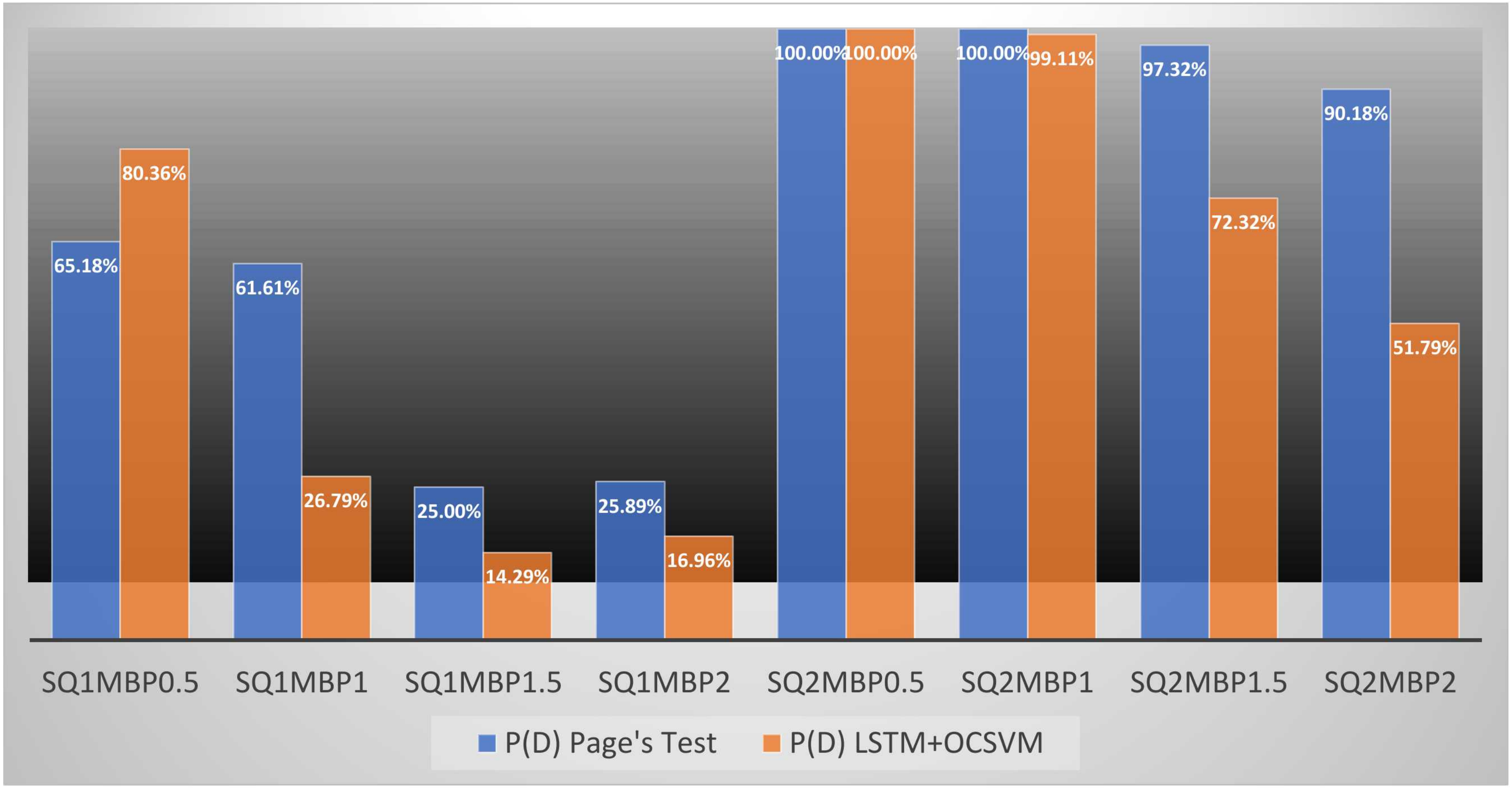
Understanding the entire machine learning pipeline



Problem setup for methodology benchmarking

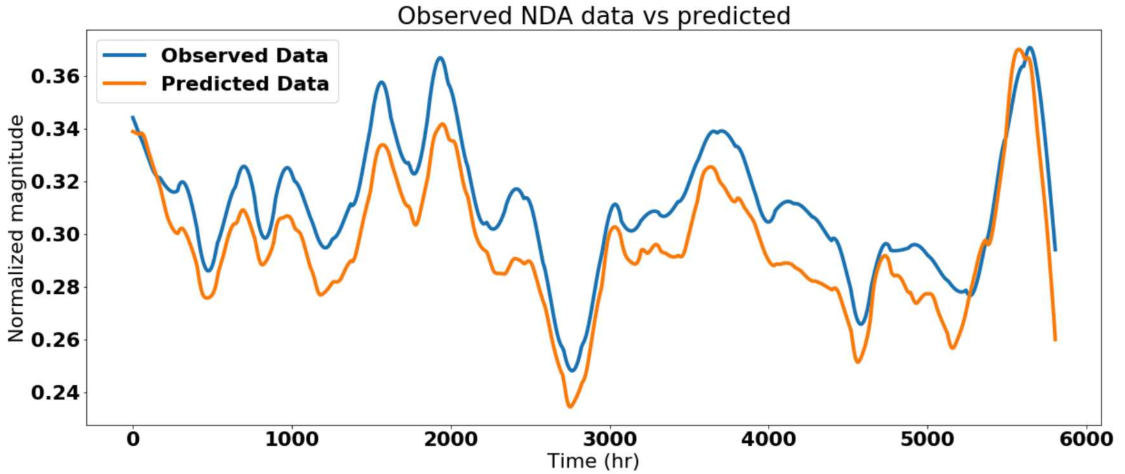
- Substitution material loss at a generic PUREX facility
  - Direct material losses can be detected through bulk mass measurements and are not considered here
- Removal of 1SQ over varying lengths of time, described as multiples of a MBP
- Masses from process model are used as inputs to the machine learning based and traditional safeguards tests
  - In practice the LSTM+OCSVM would use gamma counts from NDA measurements, but for initial work mass was used to reduce computational overhead of computing gamma spectra via GADRAS
- The LSTM+OCSVM has input/output measurement uncertainties of 1% for both systematic and random errors
- Page's trend test on SITMUF (traditional safeguards test for detecting material loss) has measurement uncertainties of ~0.7% (varies by location).
- LSTM+OCSVM is setup around a small part of one MBA, Page's trend test on SITMUF is around entire MBA
- Material loss performed after a mixing tank – challenging to detect with changing fuel characteristics such as burnup and initial enrichment

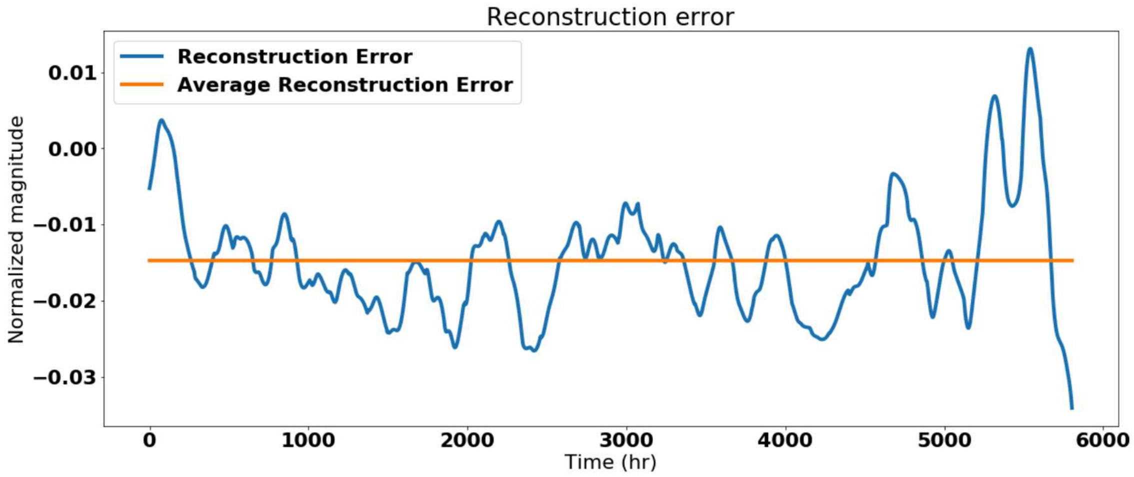
Initial results show new methodology perform better for abrupt cases but worse for protracted



Interpreting algorithm performance and understanding the role of systematic uncertainty

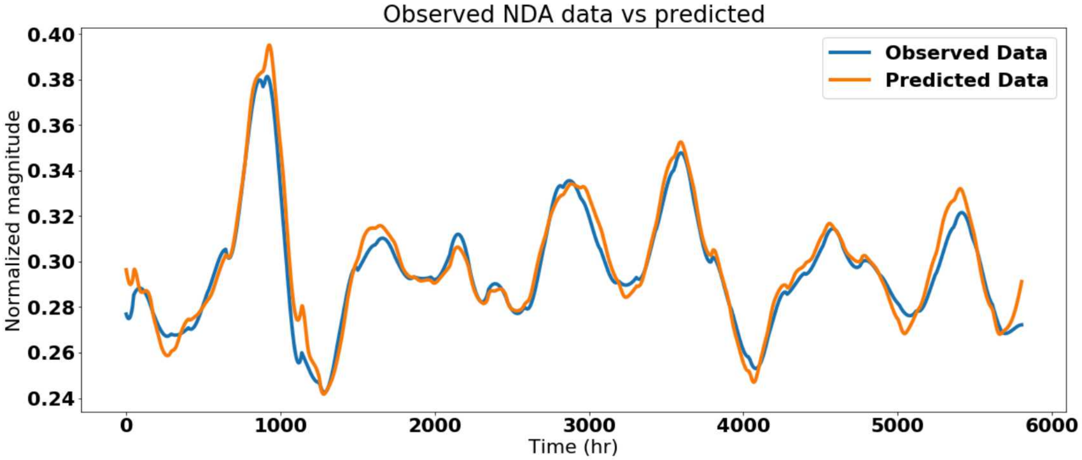
- LSTM is trained on past input data only to predict the output
- LSTM has no knowledge of the systematic error on the output stream
- Predictions based only on systematic error of input
- Negative biases in reconstruction error can occur when the systematic error is positive for the input and negative for the output
- Biases in reconstruction error can reduce probability of detection for material diversion

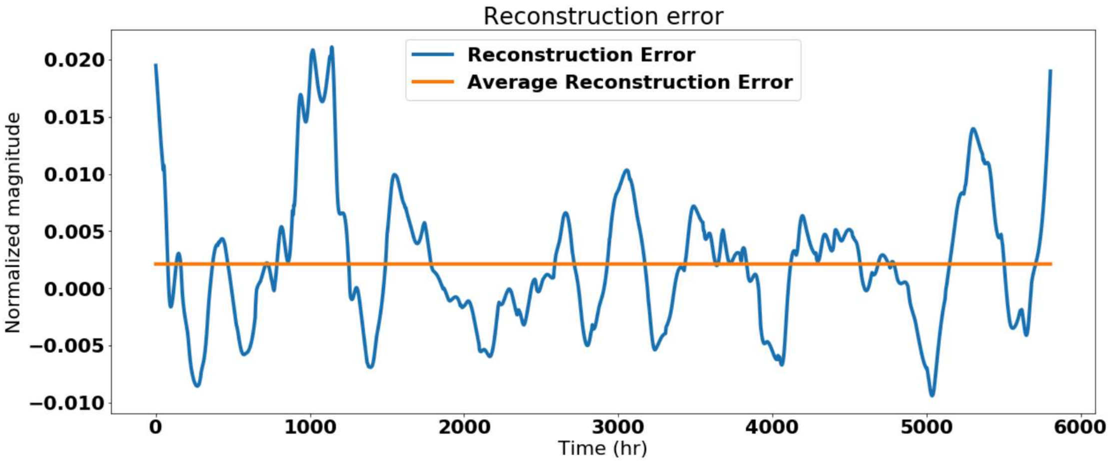




Removing the bias from the data after observation is very challenging

- Desired behavior is that the reconstruction error is centered around zero
- In practice determining the difference between systematic errors for different detectors can be challenging
- Calculate running mean?
  - Can be biased by long off-normal events
- Certified calibration period?
  - Approximate the average reconstruction error
  - Expensive and time consuming
- Cross-calibration is a possibility

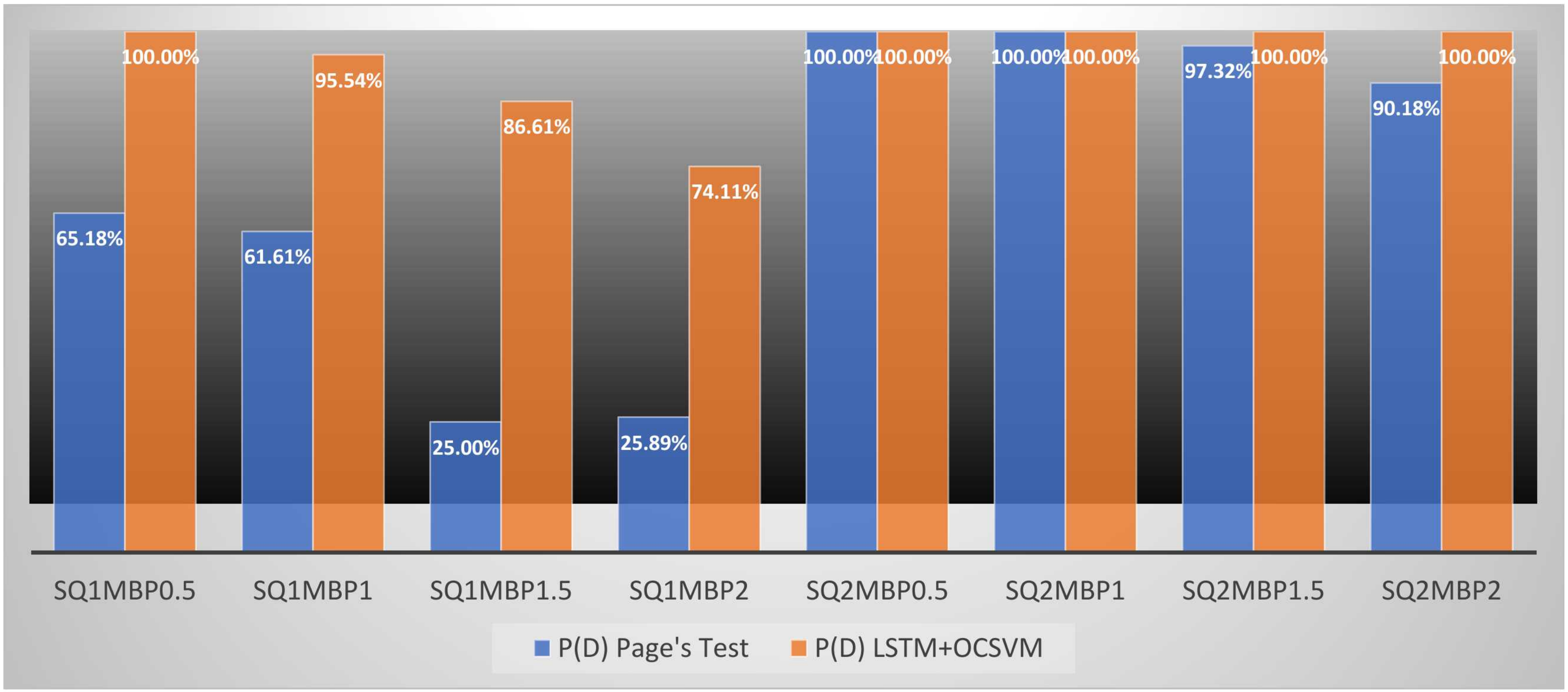




Cross-calibration could be used as a means to reduce differences in systematic uncertainty

- Current performance issues caused by differences in systematic errors for input and output measurements
- LSTM+OCSVM methodology uses deviations from a normal pattern to detect off-normal conditions
- Wide data distributions reduce the effectiveness of the approach
- Cross calibration to reduce the mismatch between input and output systematic error is one possible approach
- Input detectors are calibrated using a check source in a fixed geometry, then, output detectors are calibrated using the input detector calibration using the same fixed geometry
- Consider the a case where the systematic error is non-zero (still 1%), but the same for both input and output measurements

Reductions in the differences between input and output systematic errors greatly increase algorithm performance



Conclusions

- Unsupervised learning could prove effective for nuclear safeguards under certain conditions
- Provided certain conditions are met, it is possible to reduce reliance on destructive analysis for safeguards
- This work is an initial look at machine learning for safeguards applications

Future Work

- Algorithm improvement
  - Strange LSTM performance observed in certain limited circumstances
- Expansion of the LSTM prediction area to include entire MBA
- Evaluation of Page's trend test under conditions where systematic error is assumed to be cross-calibrated
- Performance testing in real-world conditions

Acknowledgements

- The authors would like to acknowledge fellow collaborators Benjamin Wilson and Thomas Grimes at Pacific Northwest National Laboratory.
- The authors would also like to acknowledge the National Nuclear Security Administration's Office of Nuclear Safeguards (NA-241) for funding this work
- There are various open source packages that made this work possible including scikit-learn, Tensorflow, and Keras made this work possible.
- Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Supplementary Slides – Before bias tabular data

Case	P(D) Page	P(D) LSTM+OCSVM	Relative Performance
SQ1MBP0.5	65.18%	80.36%	15.18%
SQ1MBP1	61.61%	26.79%	-34.82%
SQ1MBP1.5	25.00%	14.29%	-10.71%
SQ1MBP2	25.89%	16.96%	-8.93%
SQ2MBP0.5	100.00%	100.00%	0.00%
SQ2MBP1	100.00%	99.11%	-0.89%
SQ2MBP1.5	97.32%	72.32%	-25.00%
SQ2MBP2	90.18%	51.79%	-38.39%

Supplementary Slides – After bias tabular data

Case	P(D) Page	P(D) LSTM+OCSVM	Relative Performance
SQ1MBP0.5	65.18%	100.00%	34.82%
SQ1MBP1	61.61%	95.54%	33.93%
SQ1MBP1.5	25.00%	86.61%	61.61%
SQ1MBP2	25.89%	74.11%	48.21%
SQ2MBP0.5	100.00%	100.00%	0.00%
SQ2MBP1	100.00%	100.00%	0.00%
SQ2MBP1.5	97.32%	100.00%	2.68%
SQ2MBP2	90.18%	100.00%	9.82%