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# New Approaches Utilizing Process Monitoring Data and Machine Learning

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National Academy of Sciences Study: Merits and Viability of Different Nuclear Fuel Cycles and Technology Options and the Waste Aspects of Advanced Nuclear Reactors

May, 2021

**SAND2021-5699 PE**

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U.S. DEPARTMENT OF ENERGY

NNSA

# Motivation

- Process monitoring data (such as bulk mass, flow, temperature, current, voltage, etc.) and additional measures (such as surveillance) are part of the overall safeguards systems—but how can we make more efficient use of this data?
- One motivation for the application of data analytics like machine learning is to reduce the cost and burden associated with safeguards:
  - Reduction of sampling and DA could significantly reduce the burden of IAEA safeguards. More use of unattended monitoring systems instead of DA (on-site laboratory) would free up IAEA resources.
  - Reduction of sampling and DA can also be useful for domestic safeguards to reduce cost for the operator.
- A second motivation is to improve plant monitoring for facilities or areas that have difficulties achieving materials accountancy goals:
  - In pyroprocessing for example where there are materials accountancy challenges, can we make more use of plant monitoring data to verify operations?

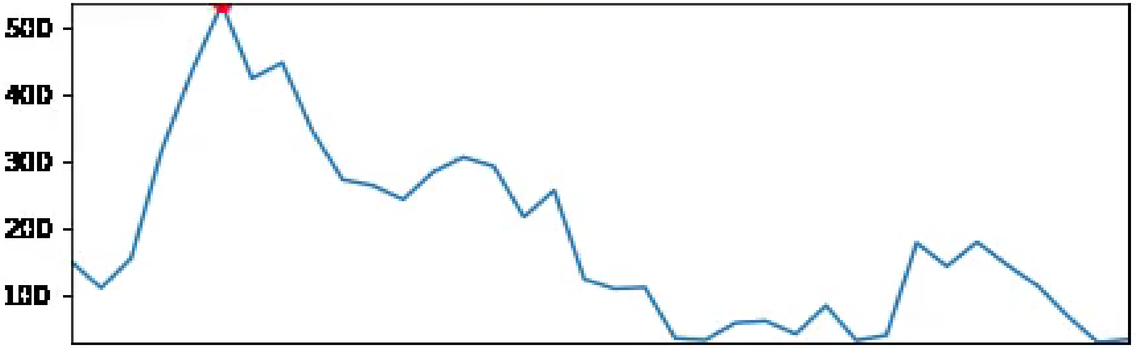
# Machine Learning: The Answer to All Our Problems

- Machine learning is broadly defined as approaches that can learn and adapt without explicit instructions.
- Potential Benefits:
  - ML can automate tedious tasks and reduce chance for human error.
  - ML can aggregate large amounts of data and disparate data sources to learn "normal" operation, potentially making it easier to detect abnormal operation.
  - Can automate monitoring to help reduce costs.
- Potential Downsides:
  - ML algorithms will only be as good as the data used to train it.
  - Developing useful algorithms potentially require a large amount of training data which may not be available.
  - A "black box" algorithm may not be suitable for safeguards where transparency is important (how much can we trust the results?)

# Example 1: Video Surveillance (NNSA Funded)

- Generates massive quantities of data with few segments of interest.
- Tedious for human review, however, image recognition is a well understood problem.

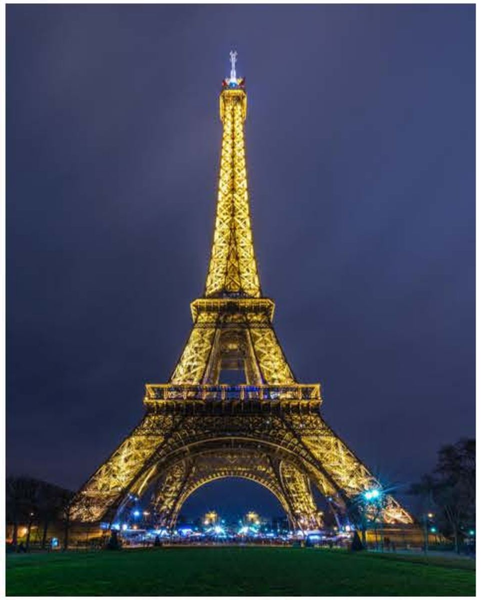
UCSD anomaly dataset:
http://www.svcl.ucsd.edu/projects/anomaly/dataset.html




Anomalous behavior identification in video sequences.

Spatio-Temporal Anomaly Detection in Video. Smith, Rutkowski, and Hamel.

# Deep Learning to Predict Operational Status (NNSA)



*Not a power plant*

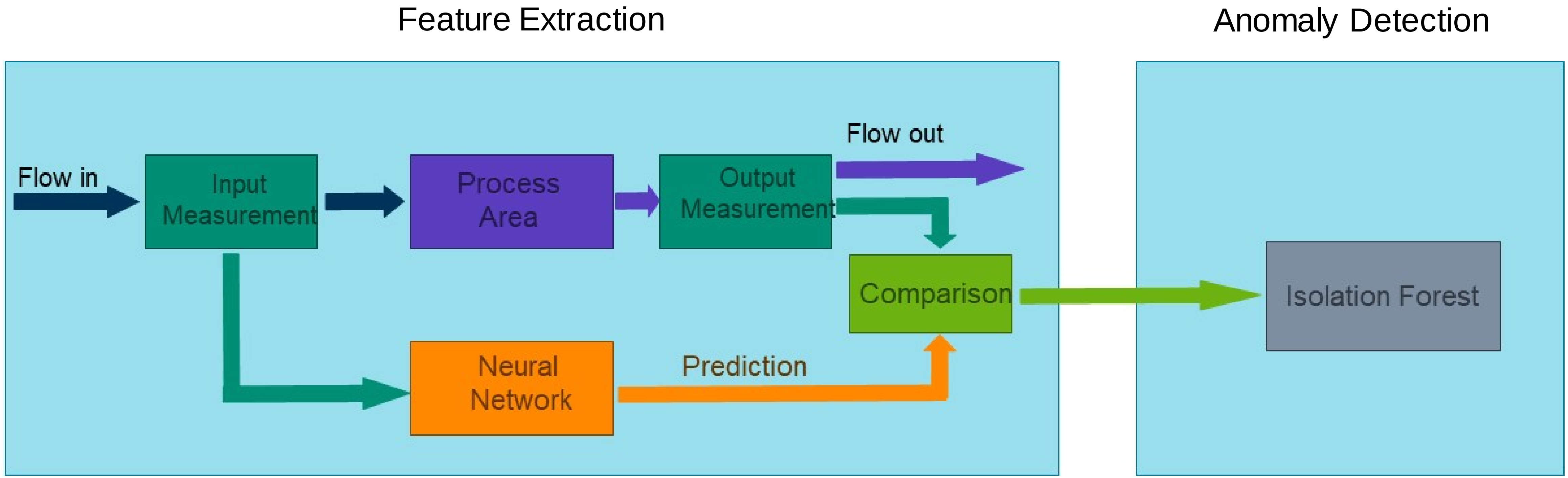
*Plant not operating*

*Plant operating*

| | Signature Precision | Operationalized Precision | Signature Recall | Operationalized Precision |
|---|---|---|---|---|
| **Plant not operating** | 0.89 | 0.66 | 0.91 | 0.87 |
| **Plant operating** | 0.96 | 0.95 | 0.95 | 0.84 |

# Example 2: Anomaly Detection in Heterogeneous Safeguards Data Streams (NNSA funded)

- Neural approaches should be able to learn normal rhythm of facility operations.
- Deviations from normal might indicate anomalous behavior.



# Example 3: Hey Inspecta! (NNSA Funded)

- Smart assistant to improve effectiveness of international nuclear safeguards inspectors.
  - Information recall
  - Measurement system integration
  - Hands-free support
- Incorporates many ML domains from text analytics to image recognition.

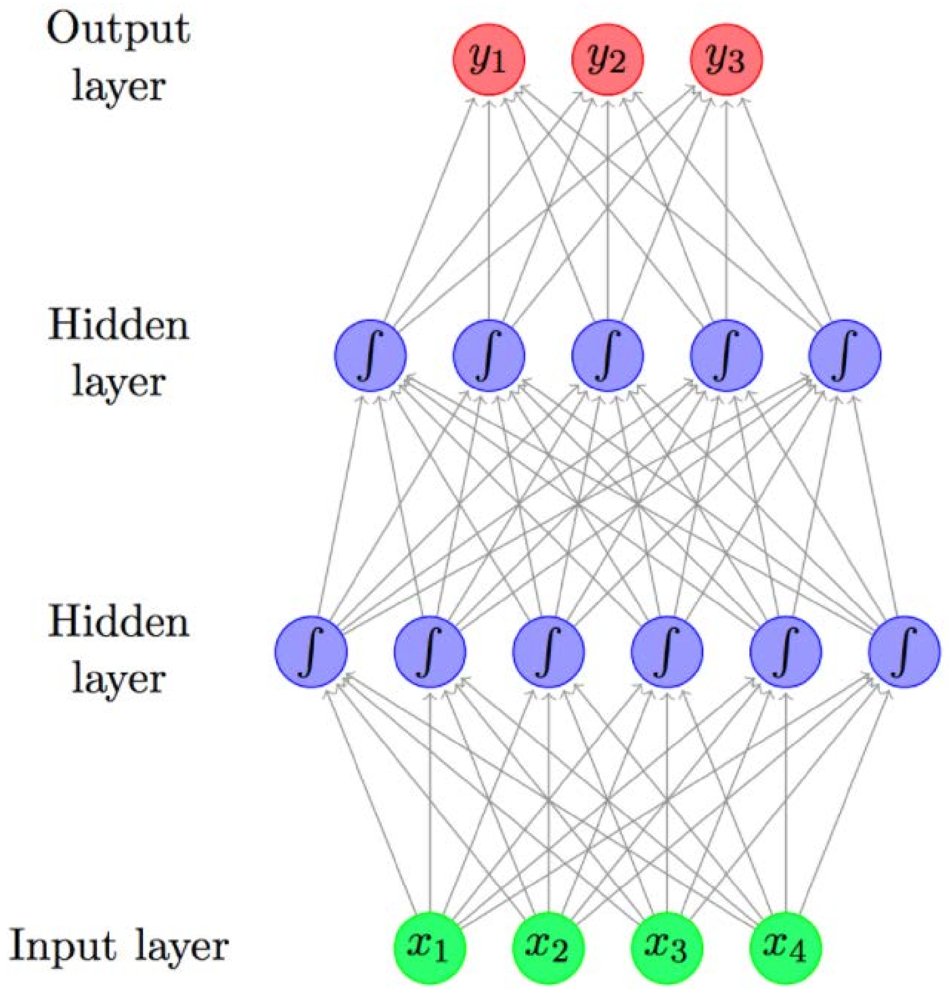


Hey Inspecta!

How can I help?

# Example 4: Neural Networks for Insider Threat Detection

- Can commercial software improve insider threat detection?
  - Changes in facility pattern-of-life
- Many off-the-shelf computing packages exist, and these can be useful in some applications.
- However, some applications in safeguards may require customized solutions.

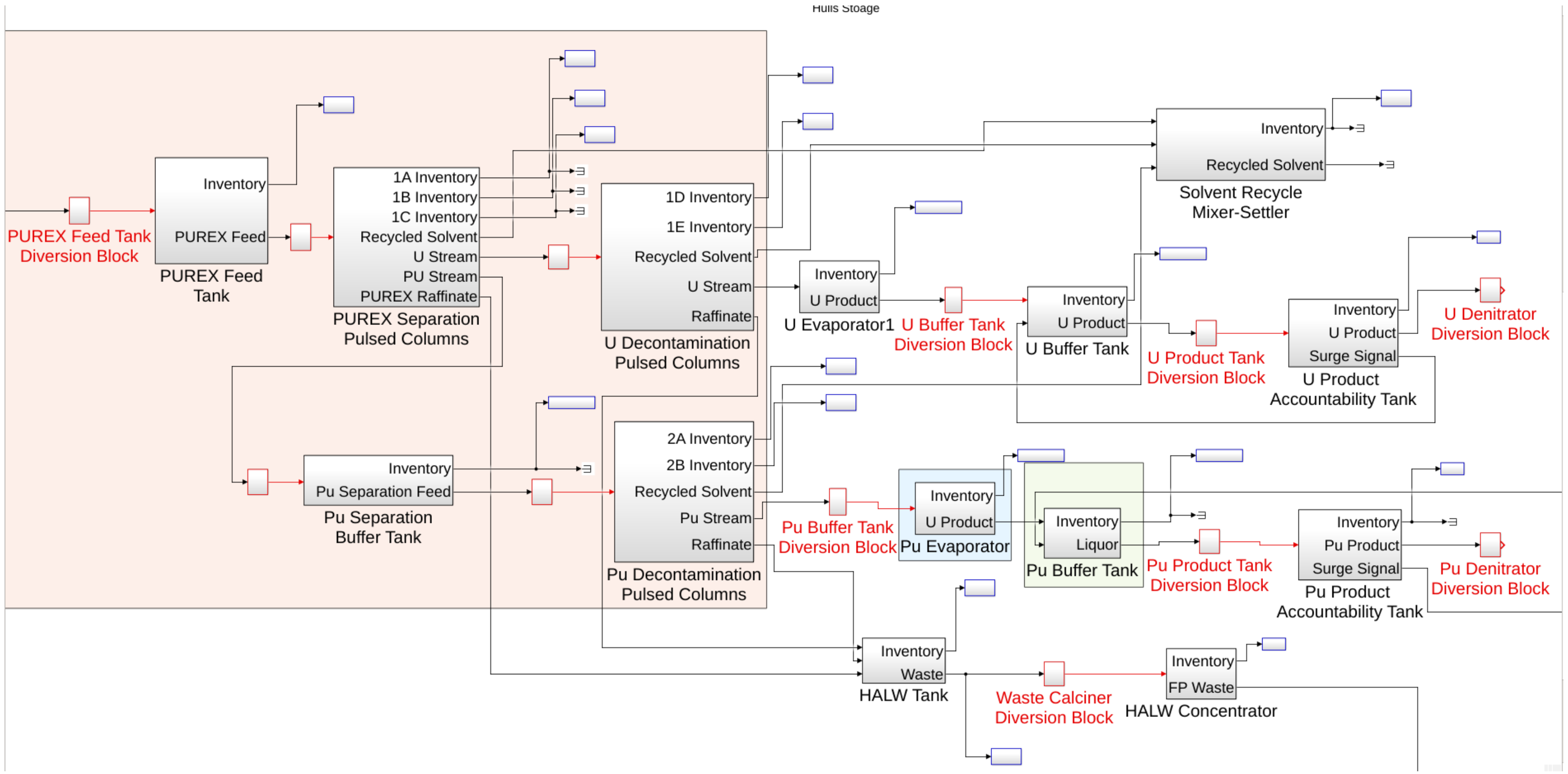



https://tutorials.com/primer-on-neural-network-models-for-natural -language-processing/

# Lessons Learned

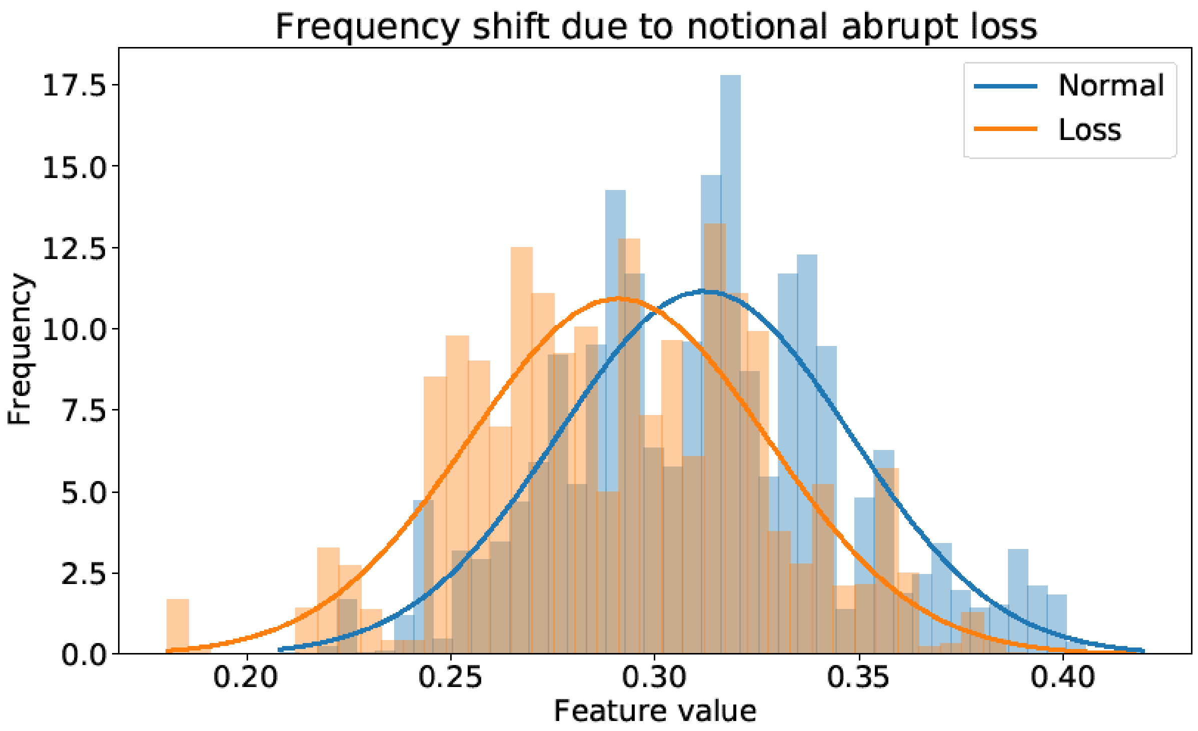
# Current and Past Work Has Evaluated the Use of ML to Improve Materials Accountancy for Reprocessing and Enrichment.

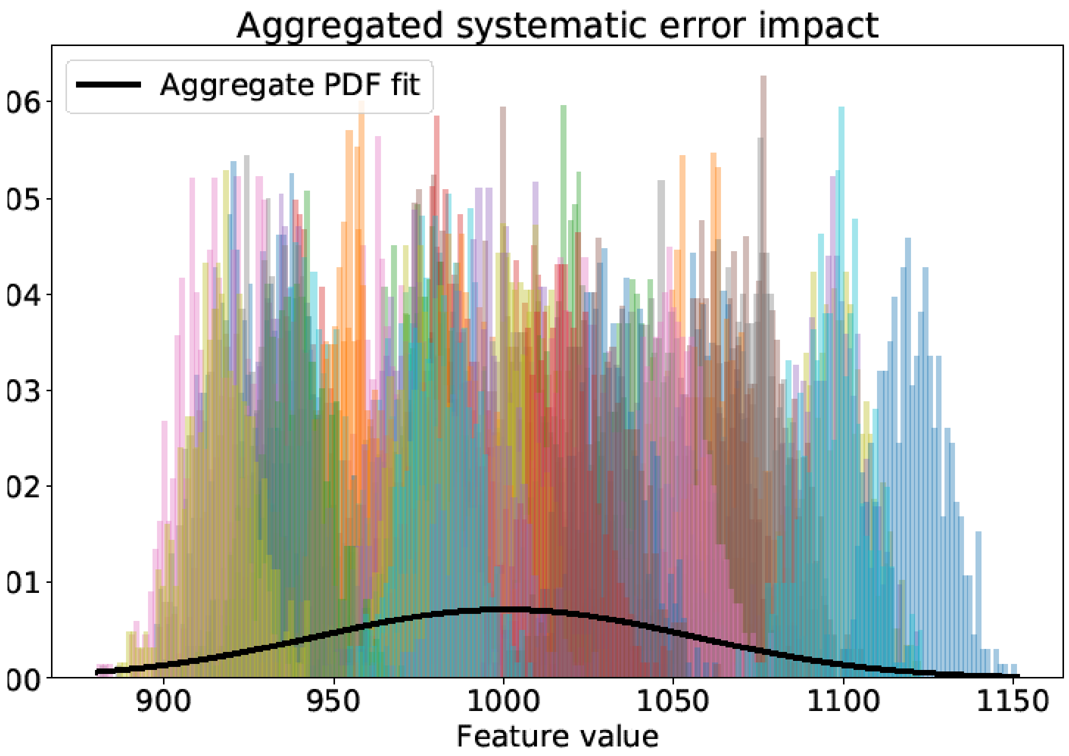
- Process models were used to generate the necessary training data.
- Simulated measurements including both bulk processing monitoring data and nuclear measurements have been used to reduce reliance on DA.



# Application of ML to Materials Accountancy

- Application of ML to a material balance (which includes measurement uncertainty) is rather unique in the ML field.
- Large data requirements combined with safeguards errors create a difficult challenge.

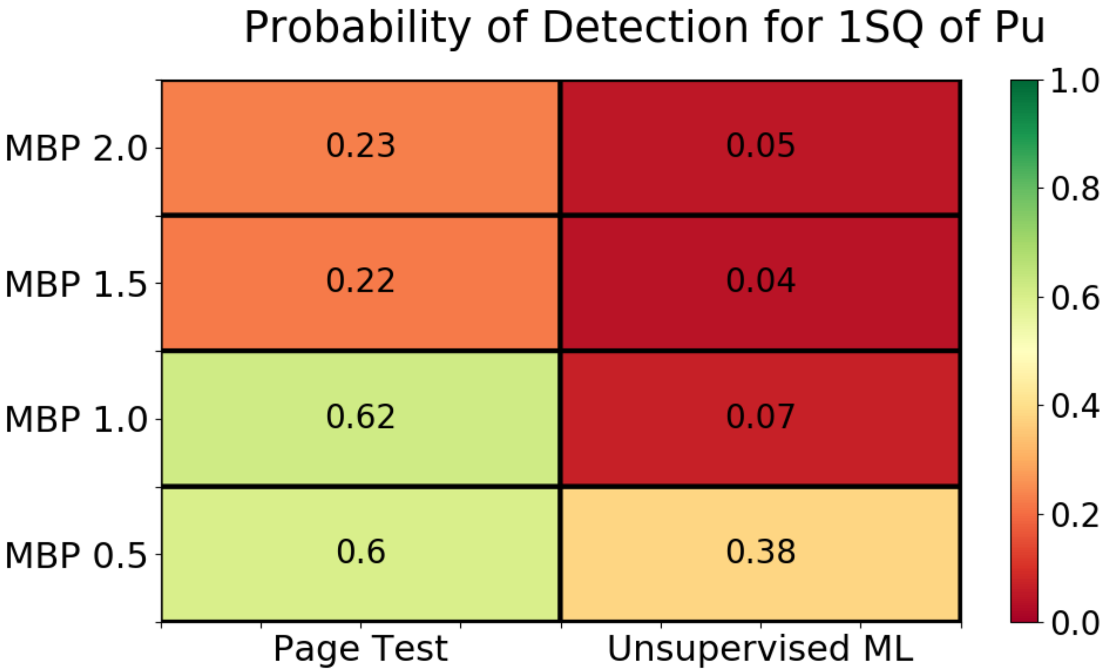


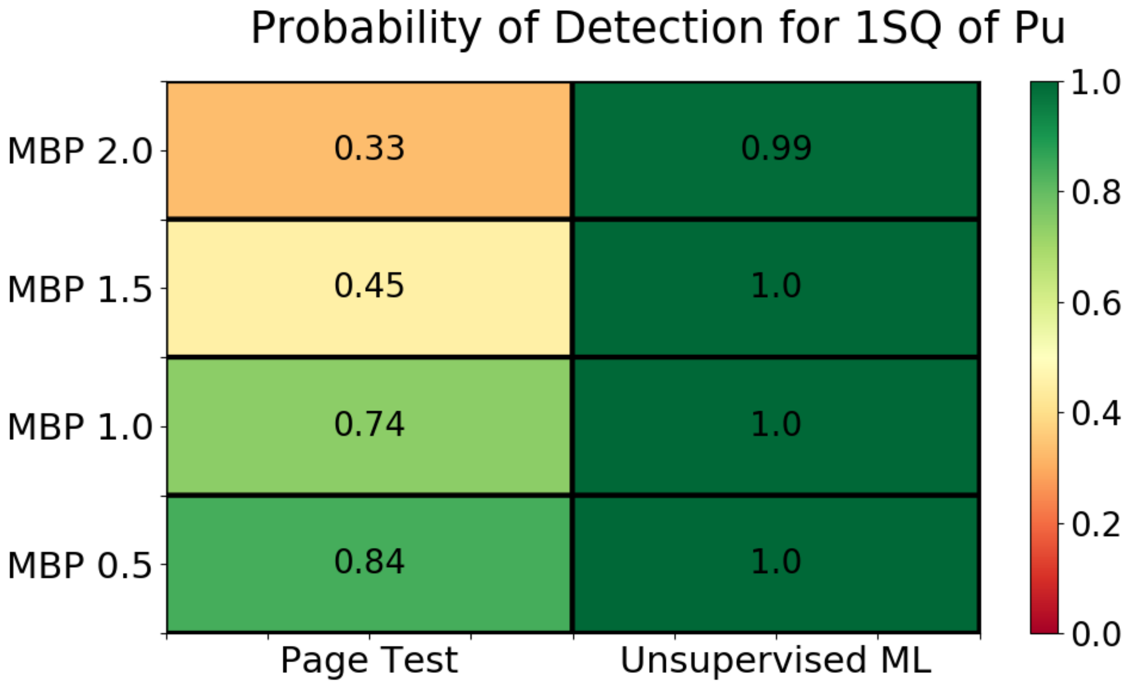
# Results

- Initially, the ML results were much worse than a traditional materials accountancy approach, due to the variation in systematic errors.
- Reduction of systematic biases through cross-calibration of sensors led to significantly improved results.

**Initial Results**




**Results with Detector Cross-Calibration**



# Conclusions

- Machine Learning can work very well in specific domains. **Image and text recognition are proven** uses with many applications. Application to containment and surveillance could provide significant benefit to safeguards.
- **ML is powerful but requires careful application and subject matter expert input**—it needs to be trained, and training can require a lot of data and time to develop the algorithms.
- The application to materials accountancy appears to be less promising—**training with data that has uncertainty is a unique application in the ML community.** More R&D is needed to determine if there are viable approaches.
- There are concerns over the **operational transparency** of using ML approaches.
- **The high consequence** nature of safeguards results in **strict requirements** not often seen in other industries which results in further R&D challenges.