Machine-Learning Techniques to Protect Critical Infrastructure From Cybersecurity Incidents or Equipment Incidents

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DSIAC Defense Systems Information Analysis Center

CSIAC Cyber Security & Information Systems Information Analysis Center

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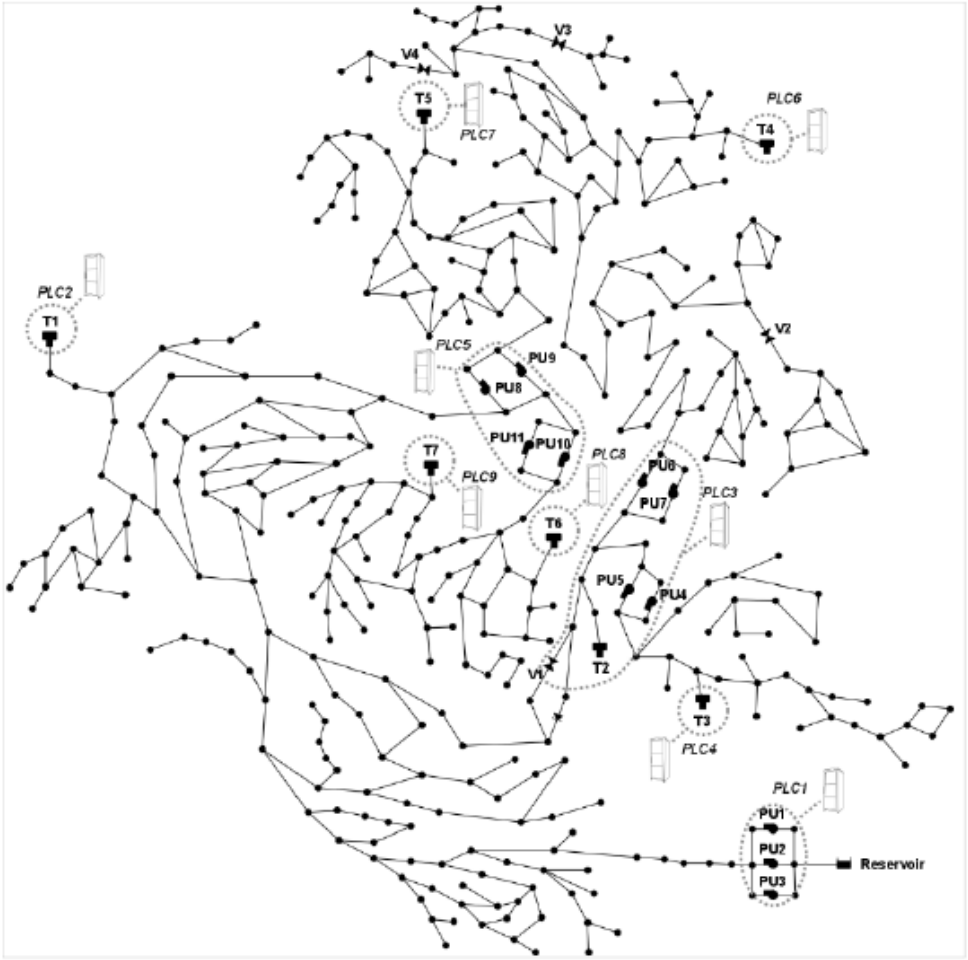
DoDIACs

Agenda

- Challenge Introduction and Goal
- Data Source
- Exploratory Data Analysis and Feature Engineering
- Solution Design
- Unsupervised Learning Approaches
- Implementation
- Anomaly Detection Results
- Conclusion

Problem Introduction

- Industrial control system cybersecurity remains a critical challenge
- Goal: detect cyber attacks on the industrial control system supporting water distribution
- Illustrate the machine learning (ML) design processes involved in solving this challenge



Data Source

- **Data from the Battle of the Attack Detection Algorithms (BATADAL) - https://batadal.net/**
- **Scenario based upon a cyber attack on a water distribution system**
- **Normal system performance data provided**
- **3 datasets provided**
  - Normal operation (8,761 rows)
  - Under attack, available for training (4,177 rows)
  - Under attack, not available for training (2,089 rows)

Data Set Sample

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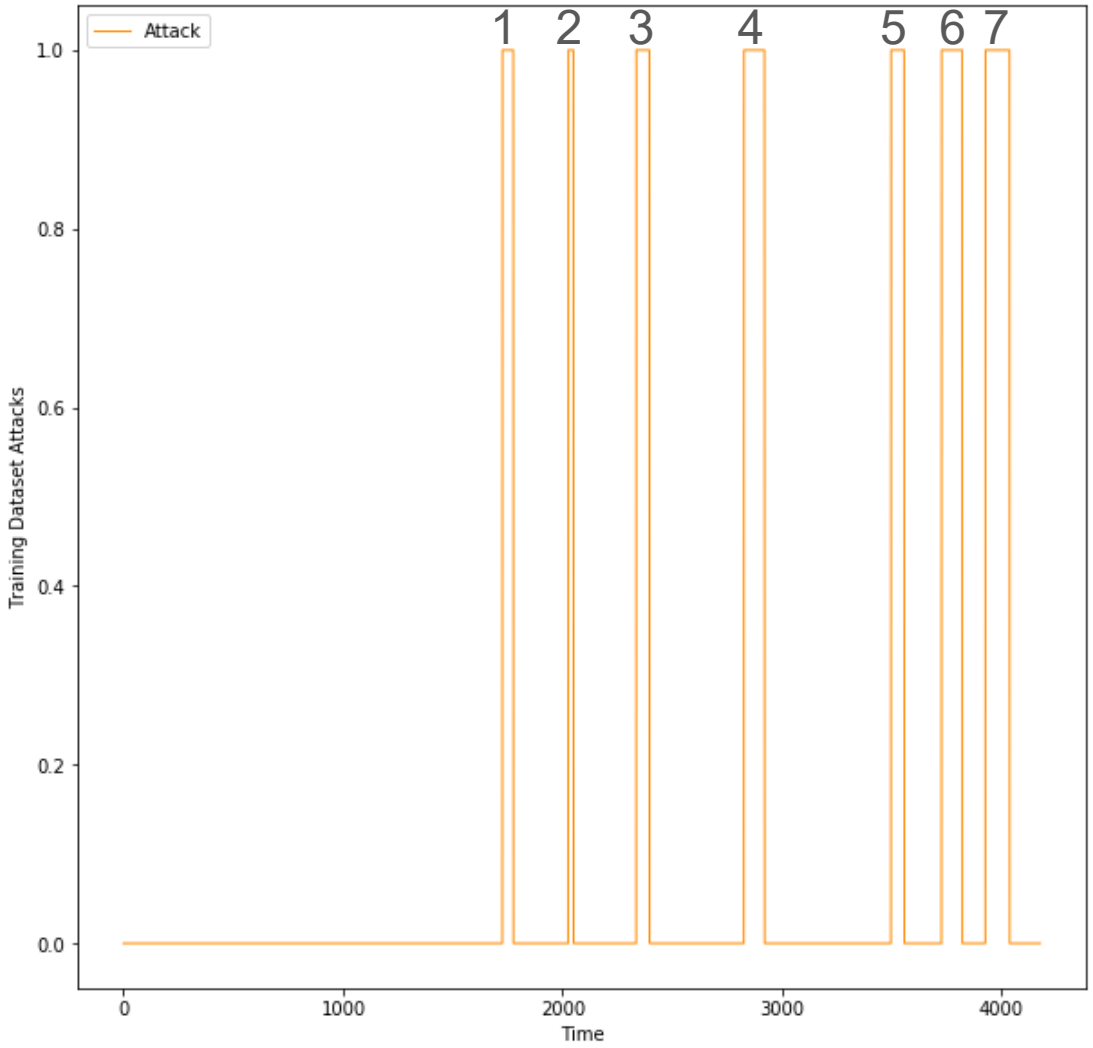
DATETIME	L_T1	L_T2	L_T3	L_T4	L_T5	L_T6	L_T7	F_PU1	S_PU1	F_PU2	S_PU2	F_PU3	S_PU3	F_PU4	S_PU4
06/01/14 00	0.50973	2.049003	3.191145	2.792634	2.656091	5.316831	1.562321	98.99844	1	99.01815	1	0	0	35.53669	1
06/01/14 01	0.41258	2.009072	3.642565	2.831673	3.126387	5.494855	1.852043	99.0959	1	99.11564	1	0	0	34.45491	1
06/01/14 02	0.320112	1.986093	4.140192	3.256733	3.574601	5.5	2.246126	98.42096	1	98.4405	1	0	0	33.48709	1
06/01/14 03	0.332879	2.009203	4.673478	3.744497	3.952379	5.5	3.203573	97.57517	1	97.59446	1	0	0	32.58554	1
06/01/14 04	0.483496	2.089049	5.237937	4.409456	3.504676	5.5	4.439714	97.35106	1	97.37028	1	0	0	31.46968	1
06/01/14 05	0.791114	2.773177	5.155802	3.937262	3.191528	5.322743	3.988906	94.13547	1	94.15375	1	0	0	0	0
06/01/14 06	1.186589	3.536068	4.983953	3.018011	2.859591	5.066728	2.977463	95.258	1	95.27661	1	0	0	0	0
06/01/14 07	1.420449	3.872926	4.747458	3.581882	2.359944	5.152646	2.953742	96.94746	1	96.96656	1	0	0	0	0
06/01/14 08	1.534827	4.138434	4.417932	3.959265	1.748313	5.395835	3.228596	96.97029	1	96.9894	1	0	0	0	0
06/01/14 09	1.576541	4.50004	4.130157	4.232002	1.666737	5.5	3.628678	97.15647	1	97.17564	1	0	0	0	0
06/01/14 10	1.55855	4.96201	3.665213	2.962582	2.107416	5.5	3.445807	97.81398	1	97.83334	1	0	0	0	0

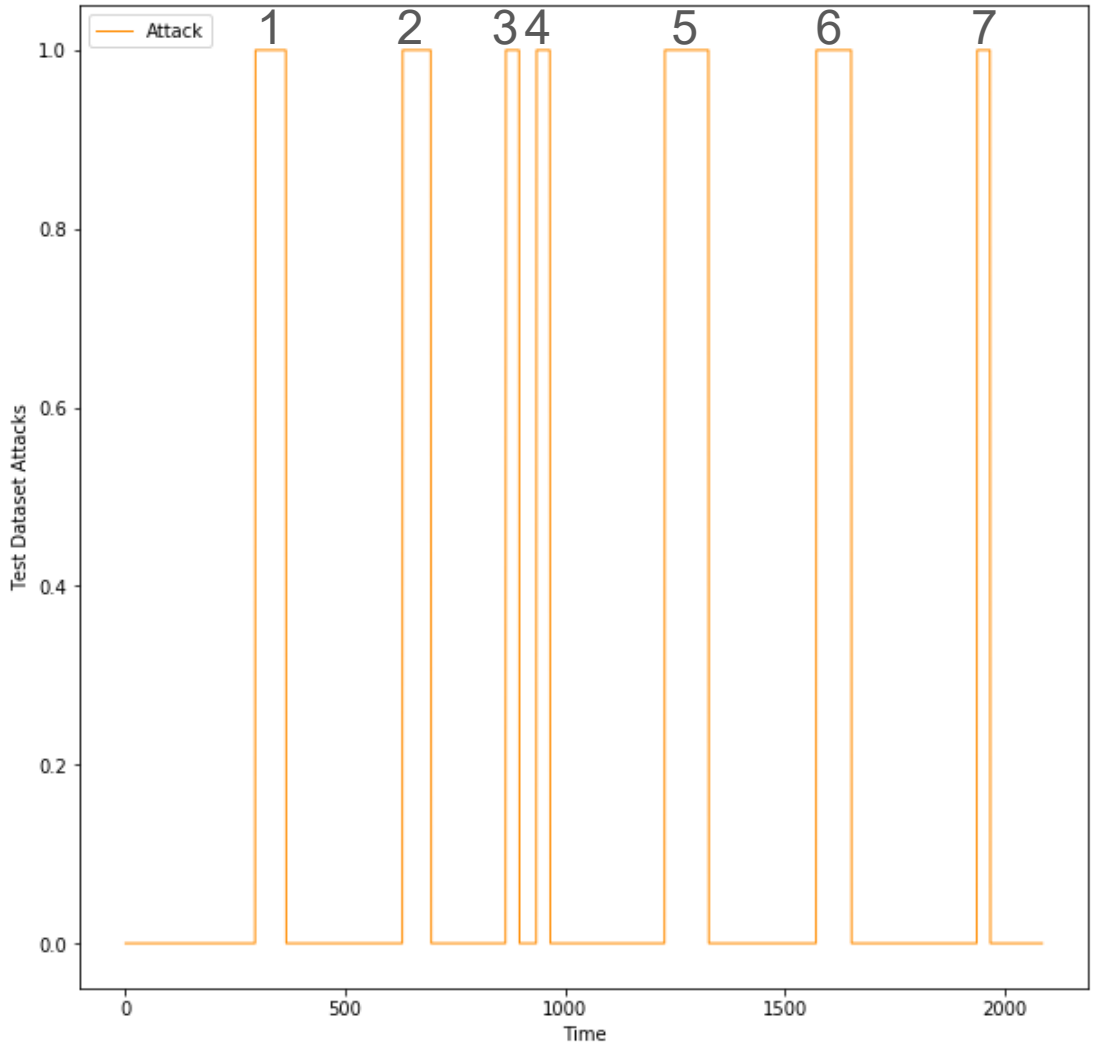
- **Each data set includes 43 input features representing:**
  - Tank levels
  - Pump switches
  - Pump flow rates
  - Valve positions
  - Valve flow rates
  - Pressures at various sensors

Attacks Conducted –Training Dataset



1. Replay attack on tank 7 level
2. Replay attack on tank 7 level and pumps 10 and 11 flow and status
3. Alter tank 1 level readings causing pumps 1 and 2 to remain on and tank 1 overflow
4. Same as attack 3
5. Speed of pump 7 reduced causing low water levels in tank 4
6. Similar to attack 5 but increased speed reduction
7. Same as attack 6

Attacks Conducted – Test Dataset

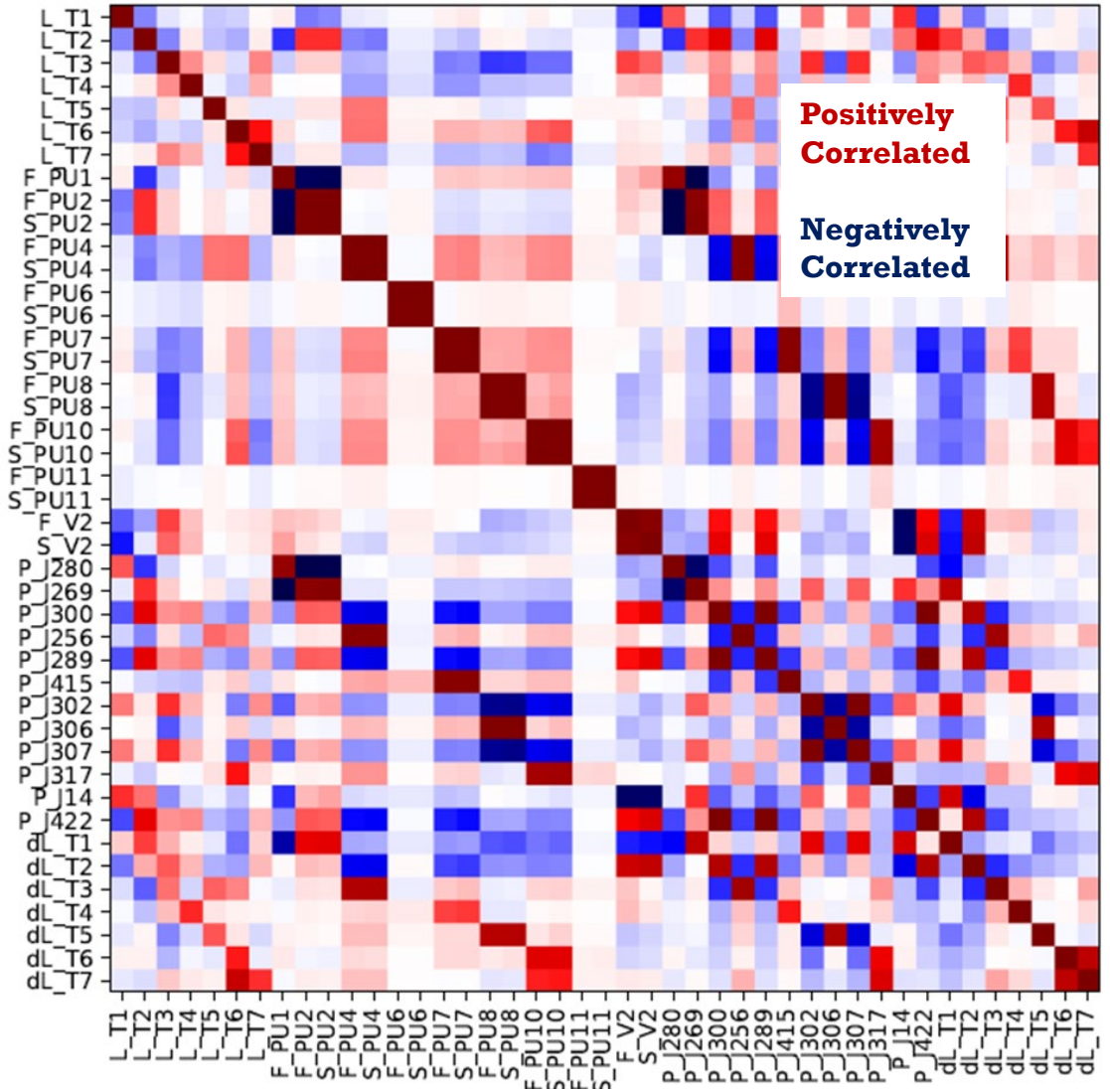


1. Replay attack on tank 3 level and pump 4 and 5 flow and status
2. Attack alters tank 2 levels causing tank 2 to overflow
3. Activates pump 3
4. Similar to attack 3
5. Similar to attack 2
6. Replay attack on tank 7 level and pumps 10 and 11 flow and status
7. Manipulation of tank level signal leading to overflow of tank 6

Exploratory Data Analysis

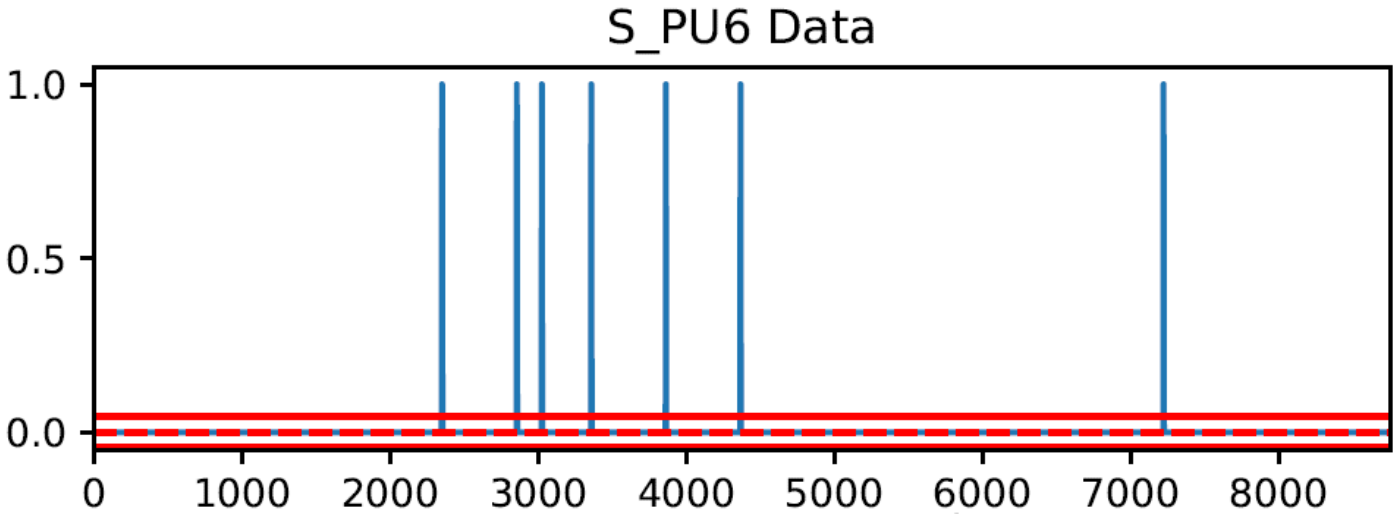
- Notable correlations
  - Correlation between pump switch and flow
  - Negative correlation between pump 1 and 2 flows
  - Correlation between tanks 6 and 7
  - Correlation between tank 3 and pump 4

- In some situations, it is useful to remove highly-correlated data
  - Breaking of a correlation might indicate an attack so they are left in
- Pump 1 is in constant use
- Pumps 3, 5, and 9 are never used
- Pumps 6 and 11 are rarely used



Feature Engineering – Sparse Features

- **Some of the data elements have significant outliers**
  - Due to only occasional equipment use
- **These can cause very high values in the normalized data and negatively impact training**
- **Solutions include limiting the magnitude of the normalized values or not normalizing these type of features**

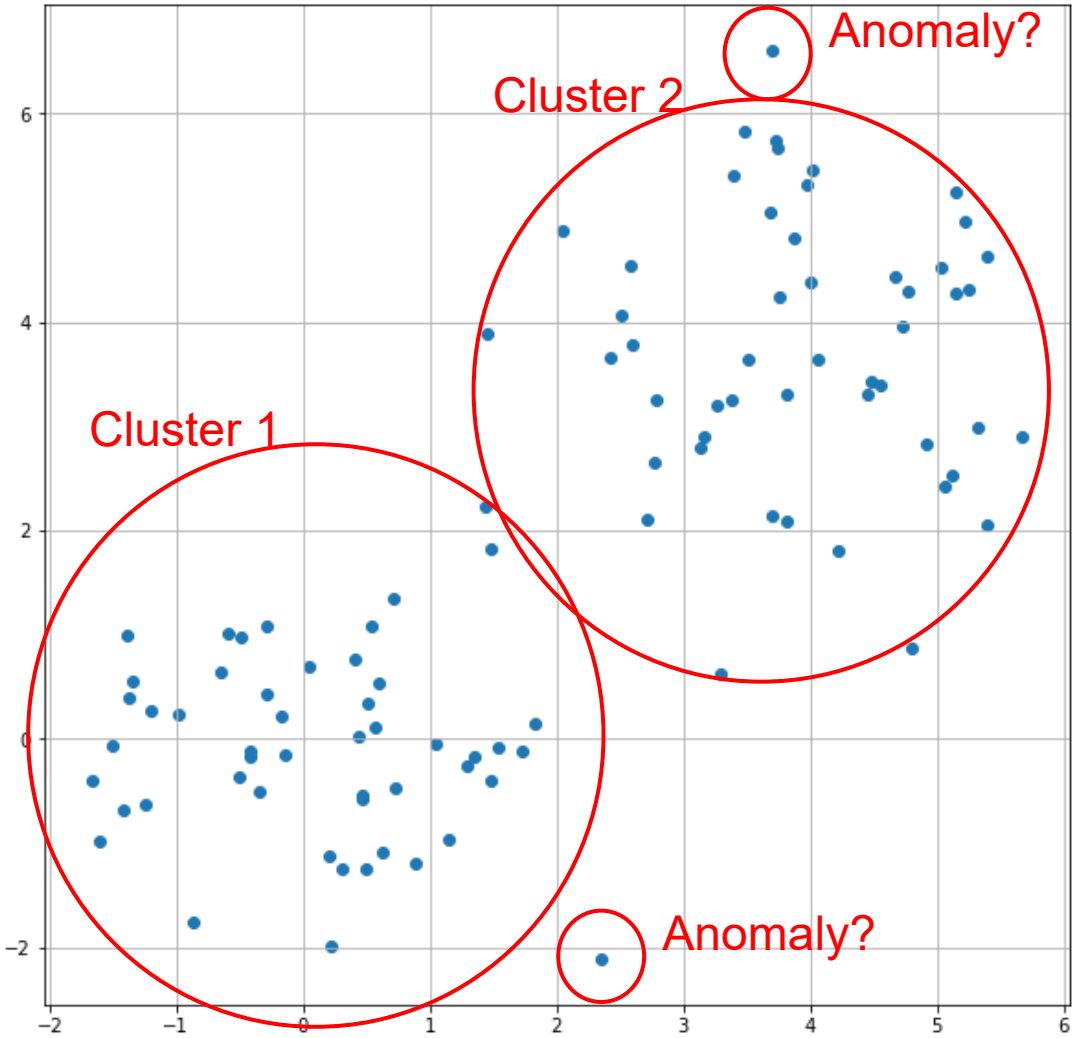


Solution Design

- **Solution architecture**
  - Data set with no attacks provided
  - Limited data with attacks provided
  - Because very little attack information was provided:
    - Use an unsupervised training method to detect data anomalies that indicate a cyber attack
- **Two unsupervised approaches investigated**
  - Clustering
  - Neural network autoencoder

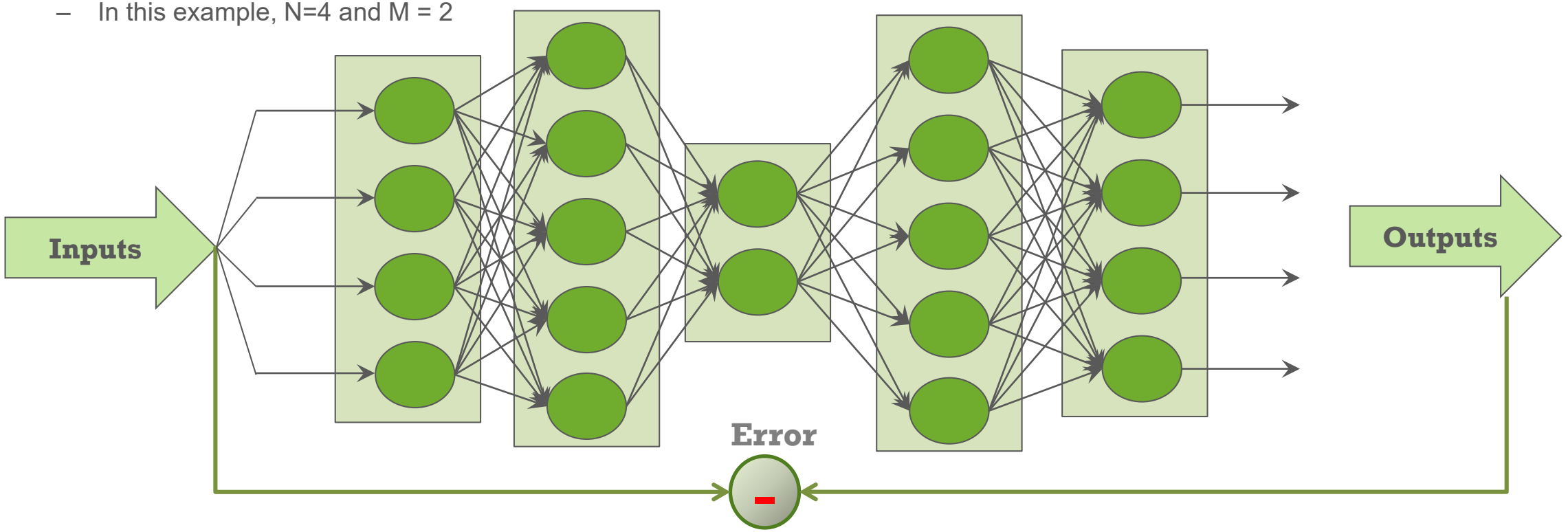
Unsupervised Learning Approaches

- **Useful for unlabeled data sets**
- **Common approaches include:**
  - **Clustering**
  - **Anomaly detection**
  - **Neural network autoencoders**
- **Capable of detecting anomalies**



Neural Network Autoencoder

- The desired output is the same as the actual input
- The network is trained to produce this output
- The compression layer in the center reduces the dimensionality from N input nodes to M center nodes
  - In this example, N=4 and M = 2



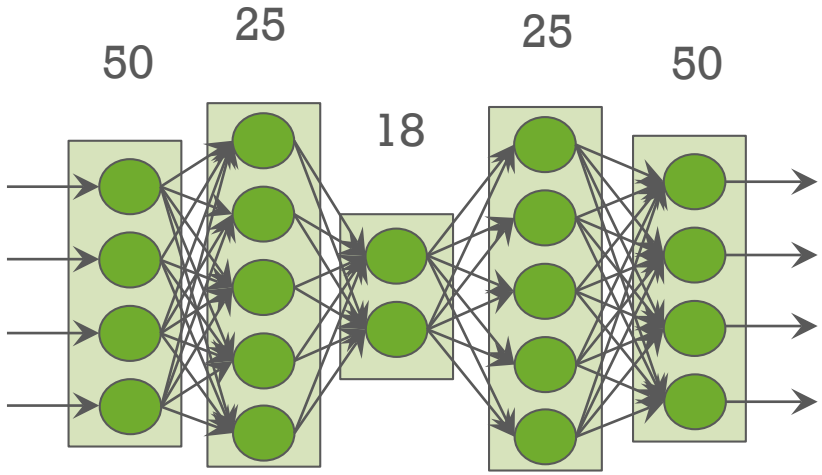
Anomalous data will produce high errors so the autoencoder can be used as an outlier detector

Solution Design (cont'd)

- **Conducted some experiments with clustering**
  - Was not on track to provide a good solution
- **Experimented with an autoencoder and this promised significant improvement**
- **Continued refinement of architecture throughout development**
  - Number of layers
  - Minimum number of nodes in a layer

Implementation

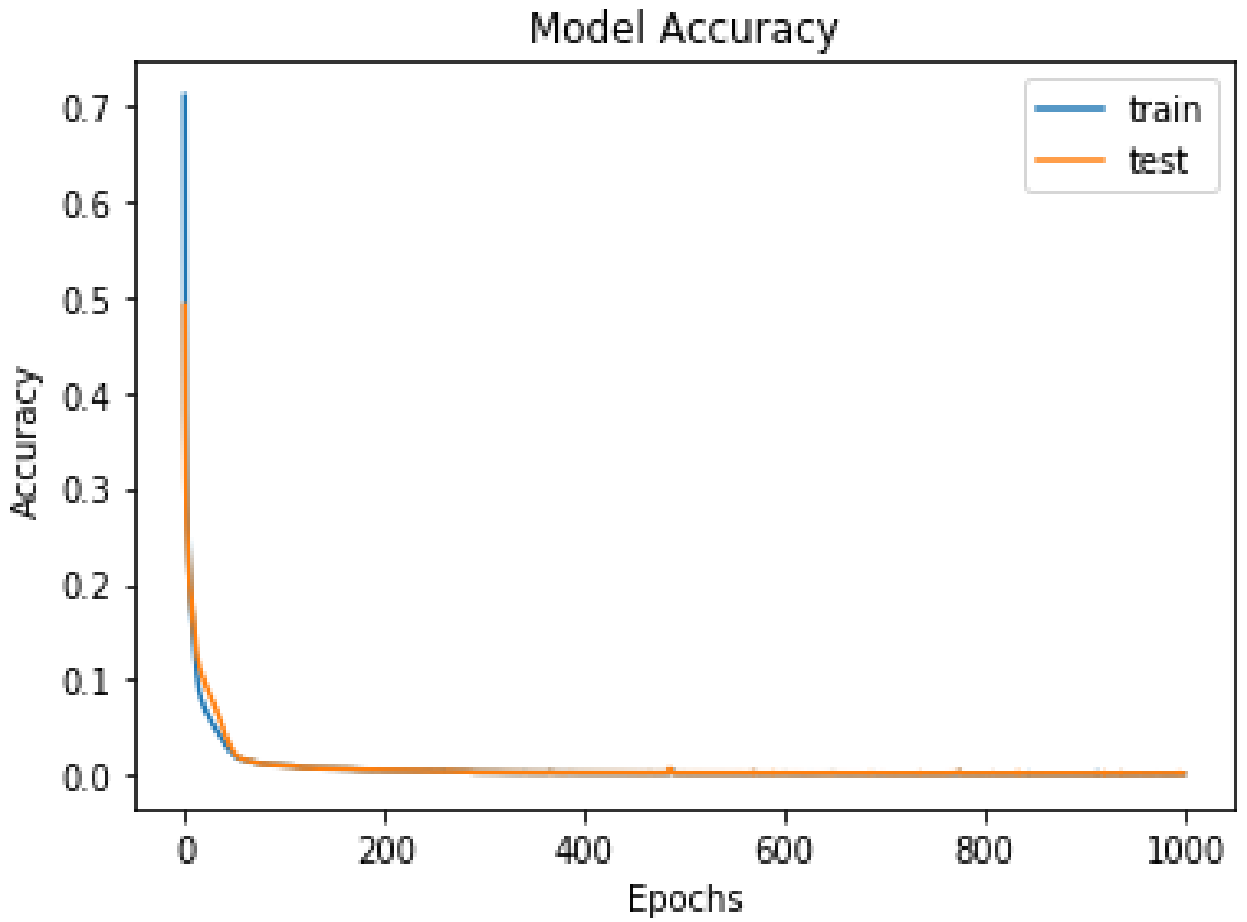
- **Used a neural network autoencoder with:**
  - 50 input nodes
  - 1 for each feature
  - An intermediate layer with 25 nodes
  - An encoding layer with 18 nodes
  - This is the compression factor
  - An intermediate layer with 25 nodes
  - A result layer with 50 nodes
  - The activation function only outputs positive values
  - An output layer with 50 nodes
  - This allows the output to handle both positive and negative values



- **Split the data into a training set with 5,869 samples and a testing set with 2,891 samples**
- **Trained the network for 1,000 epochs (complete passes through the data)**

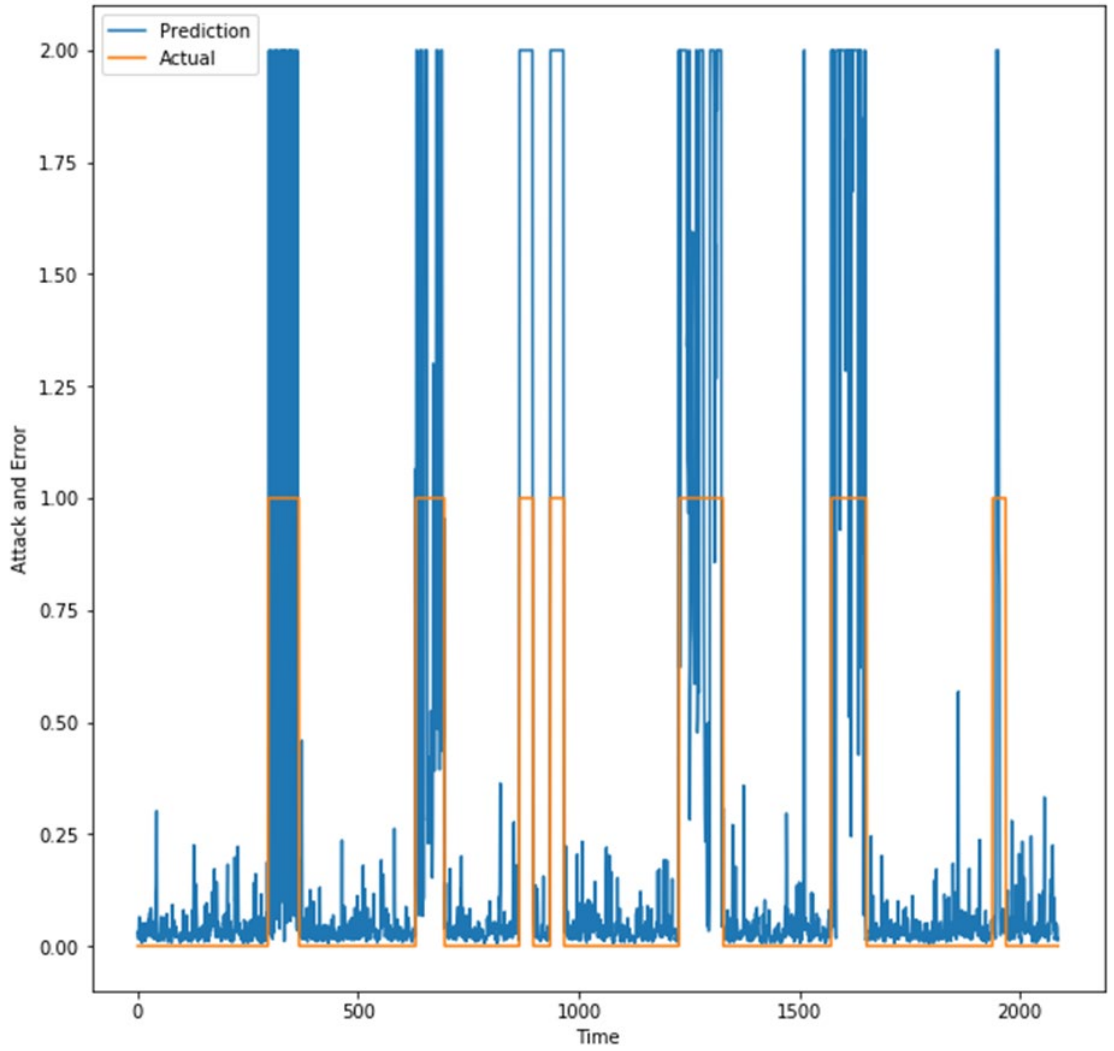
Implementation

- Trained model
- Reduced mean squared error to more than 99.8%
- Completed on a business-class laptop in less than 2 minutes



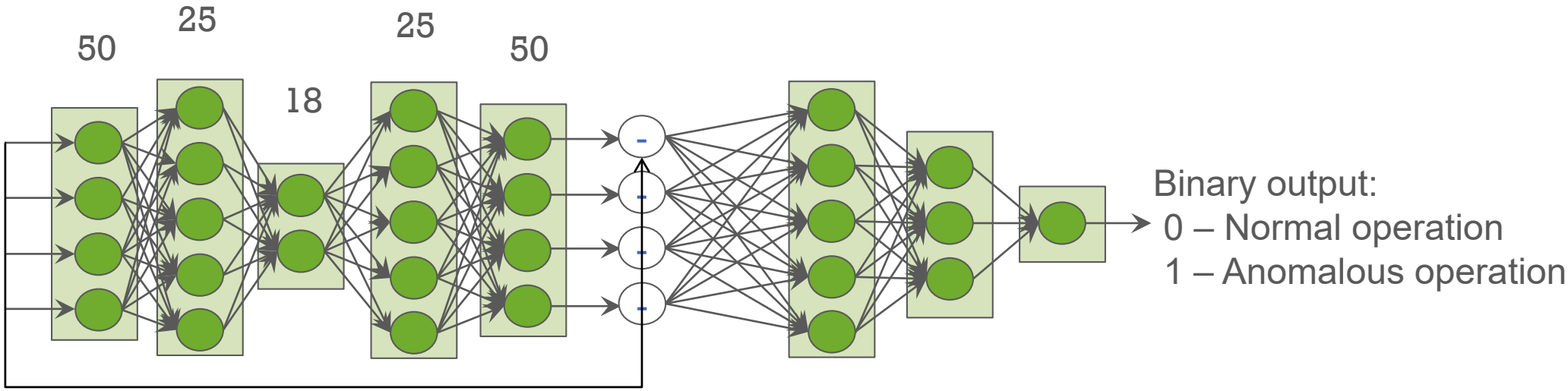
Initial Results

- **Blue line indicates the magnitude of the error between the input and output of the autoencoder**
- **Orange line indicates the actual attacks**
- **Generally good detection of the hacks**
  - 1 false positive
- **Areas for improvement**
  - Data preprocessing
  - Addition of neural network post-processing layer



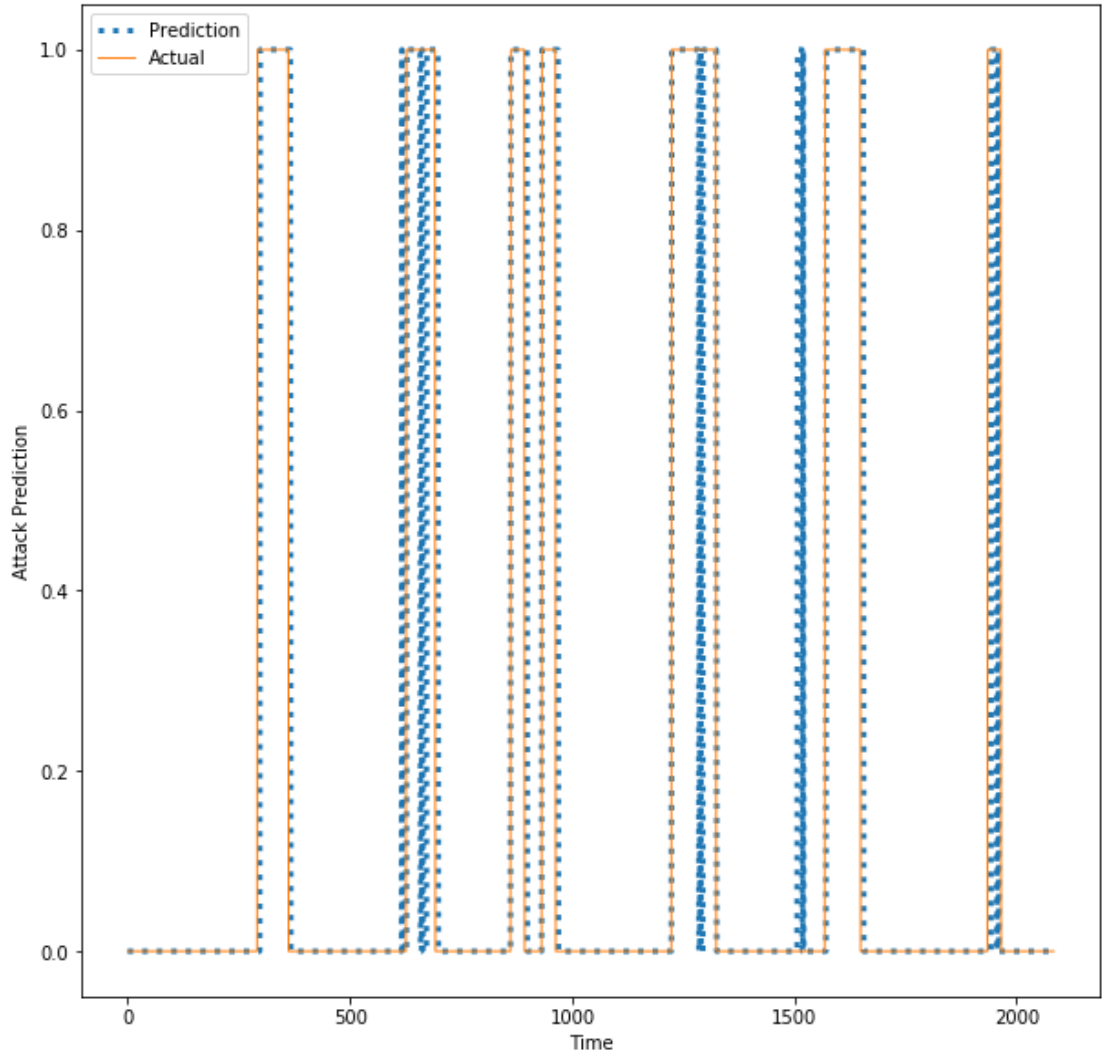
Neural Network Post Processing

- **Implemented a two layer neural network that post-processed the autoencoder error**
  - Output - Input
- **Both a binary classified and a regression model were tested**
  - Binary classifier performed better



Results (cont'd)

- **One false positive remains**
- **System able to reliably detect cyberattacks**
- **Areas for improvement remain:**
  - Localize the components impacted by the intrusion
  - Improve handling of infrequent events



Conclusion

- **Autoencoder approach able to successfully detect performance anomalies in an industrial control system**
- **Results achieved despite relatively small data set**
- **Improvements to approach planned:**
  - Better rejection of false positives
  - Identification of specific equipment being targeted

Questions

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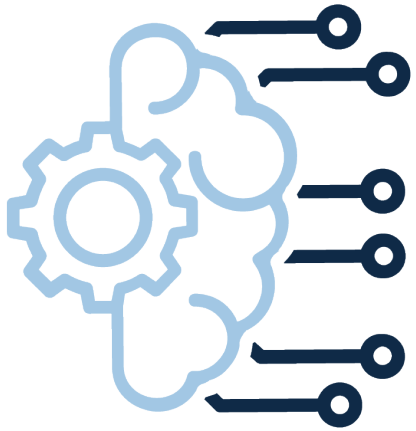

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