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# Towards Robust Power Grid Attack Protection using LightGBM with Concept Drift Detection and Retraining

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# Overview



- In this work we present a robust methodology to detect cyber attacks on the Power Grid
- Issues with the state-of-the-art methods:
  - Model-based approaches lack scalability and accuracy
  - Focus mostly on binary (attack/no attack) events, ignoring natural events
  - Machine learning-based model accuracy reduces overtime
- In this work:
  - We employ a realistic testbed to expose all attack surfaces of the platform
  - We use a Three-Class classifier (no attack/natural event/attack)
  - We introduce concept drift to maintain the model accuracy in the long-term

# Proposed Base Classifier: LightGBM

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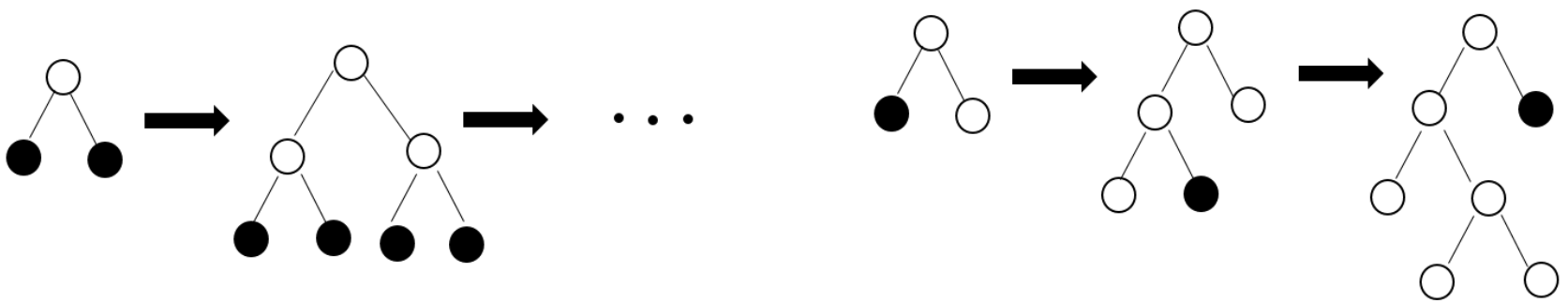
- Ensemble Learning
  - Multiple learners are trained in sequential or parallel way
  - LightGBM: Light Gradient Boosting Machine
    - LightGBM excludes data instances with small gradients
    - Converges faster and accurately



# Threat Model



- Assumptions
  - Attacker has control over monitoring data
  - Compromised devices may be protection/monitoring or networking
- Examined attack scenarios:
  - Data injection: Change phasor values in synchrophasor packets
  - Remote tripping injection: Sending close/trip command using relays
  - Relay setting change: Change the configuration of relay i.e. CT, VT ratio

# Training Dataset



- Benchmark Dataset[1]
  - Consists of 3 bus system and 4 circuit breaker
  - Buses equipped with relays to control the circuit breakers
- Dataset description
  - *Scenarios*: Dataset consists of 37 scenarios
  - *Events*: Dataset broadly categorized as No Events, Natural, and Attack Events
  - *Features*: Comprises of 128 features correspond to phasor and magnitude of voltage and current

| Feature | Description | Importance |
|---|---|---|
| R2-PA6:IH | Relay2 Current Phase Angle | 0.020763 |
| R2-PA3:VH | Relay2 Voltage Phase Angle | 0.019436 |
| R3-PA6:IH | Relay3 Current Phase Angle | 0.019231 |
| R2-PA7:VH | Relay2 Voltage Phase Angle | 0.019213 |
| R1-PM5:I | Relay1 Current Phase Magnitude | 0.019079 |
| snort_log | Log collected by IDS | 0.000000 |
| control_panel_log | Log collected by control panel | 0.000000 |
| R2: S | Status Flag for relays | 0.000000 |
| R3-PA9:VH | Relay3 Voltage Phase Angle | 0.000086 |
| R4-PA9:VH | Relay4 Voltage Phase Angle | 0.000089 |

| Class | Description | Event Type | Scenario Id. |
|---|---|---|---|
| 0 | Normal operation load changes | No Event | 41 |
| 1 | SLG Faults, Line Maintenance | Natural Event | 1-6,13,14 |
| 2 | Data Injection, Remote tripping, Relay setting change | Attack Event | 7-12,15-20, 21-30, 35-40 |

[1] https://www.sites.google.com/a/uah.edu/tommy-morris-uah/ics-data-sets

# Feature Selection



- Accuracy of reduced feature set and overall set
  - Accuracy of model trained from selected features is better
  - In multi-class accuracy increases with more features
- Other features
  - Number of iterations: 8000
  - Max_depth: 9, num_leaves: 50
  - boosting_type: Gradient Boosting (GDBT), Gradient-based One Side Sampling (GOSS)

| Features \ Label | Binary-Class | Three-Class | Multi-Class |
|---|---|---|---|
| All | 96.9 | 95.3 | 92.65 |
| Subset | 97.3 | 97.1 | 91.2 |

# Model Generation and Concept Drift

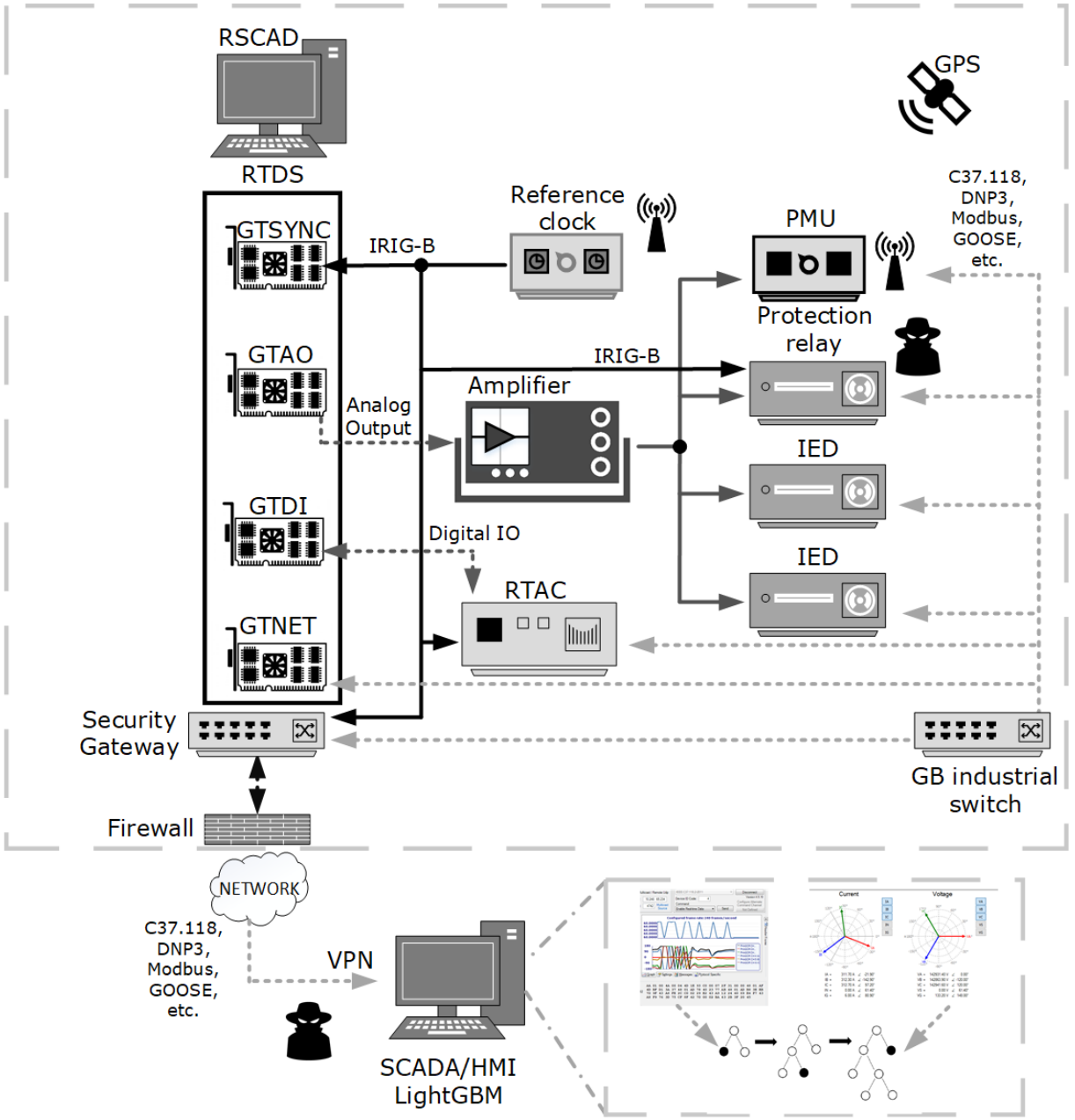


- Detect accuracy reduction
  - Divide dataset in chunks
  - Pass data to Massive online Analysis (MOA)[2] framework
  - Drift Detection Method and Early Drift Detection Method
  - Detection of drift at instances where accuracy is reduced substantially
- Retraining of model
  - LightGBM classifier is retrained based on drift detection
  - Model accuracy increases in fraction

[2] A Bifet, G Holmes, R Kirkby, and B Pfahringer. 2010. MOA: Massive Online Analysis. J. Mach. Learn. Res. 11 (2010)

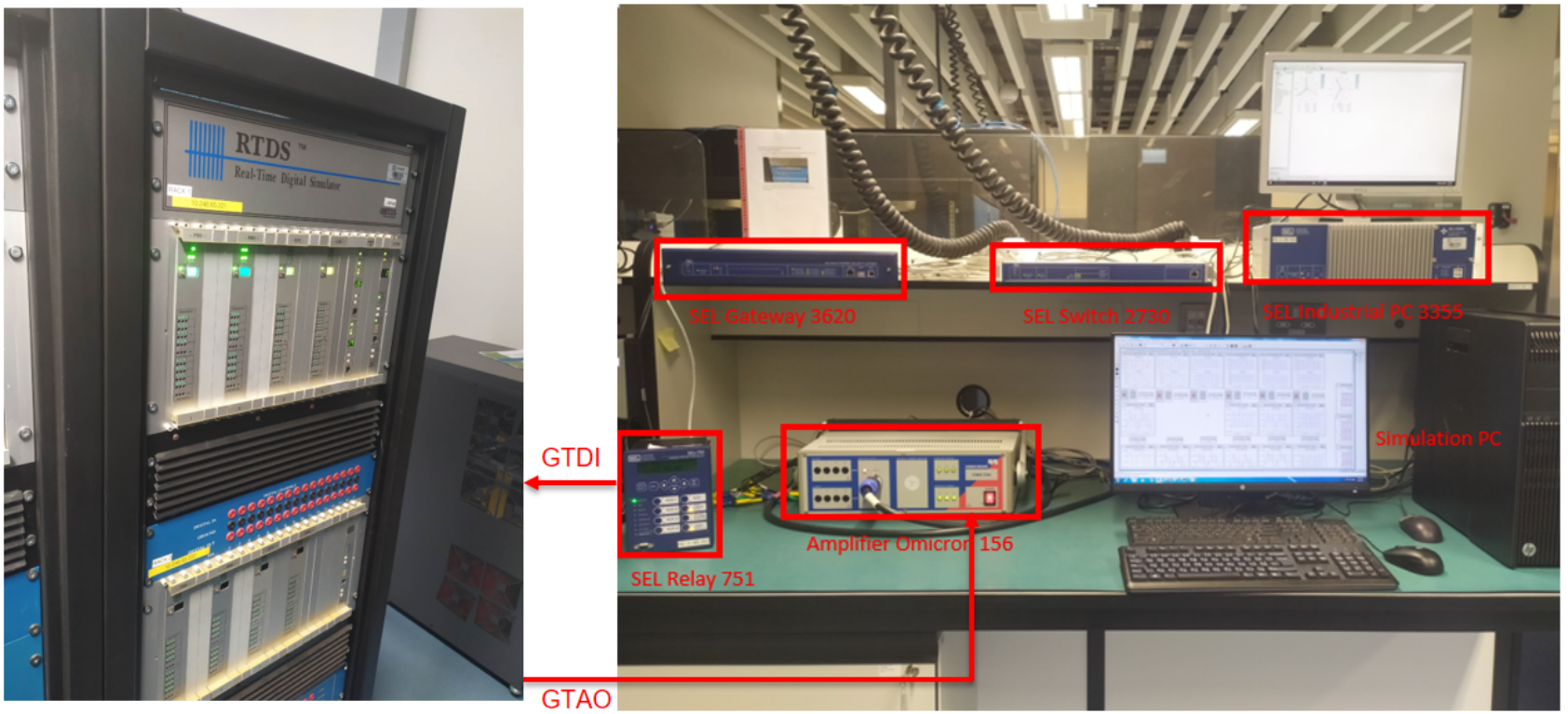
# Experimental Setup Schematic View





# Experimental Setup Physical View





# Model Detection Accuracy



- Evaluation Metrics and detection
  - Compare results against other machine learning approaches
  - Used Binary, Three, and Multi class label data

| Boosting Classifier | DNN | | | SVM | | | LightGBM (Our work) | | |
|---|---|---|---|---|---|---|---|---|---|
| [M] \ [L] | B | T | M | B | T | M | B | T | M |
| **Precision** | 68.53 | 61.26 | 10.36 | 83.17 | 79.05 | 20.64 | 97.38 | **96.99** | 93.11 |
| **Recall** | 78.16 | 78.26 | 13.48 | 78.57 | 78.57 | 24.34 | 97.38 | **96.98** | 92.76 |
| **F1 Score** | 68.86 | 68.72 | 6.01 | 69.44 | 69.43 | 19.05 | 97.38 | **96.98** | 92.76 |
| **Accuracy** | 78.16 | 78.26 | 13.48 | 78.57 | 78.57 | 24.34 | 97.28 | **96.98** | 92.76 |

[M]: Metrics, [L]: Labels, B : Binary Class, T : Three Class, M : Multi Class

- Dynamic retraining of model after drift detection
  - Retrain model after 50% accuracy loss
  - Binary classification and Three class accuracy increased to 98.02% and 97.73% respectively

# Related Work Comparisons



- We compare against emulated or physical power system
  - LightGBM outperforms other boosting techniques
  - Existing solutions do not employ concept drift
  - Our method performs best in three class data

| Related Work | Classifier | Label | # of features | Acc. | CD |
|---|---|---|---|---|---|
| Our Work | LightGBM | T | 128 | 97.73% | ✓ |
| [26] | Adaboost | M | 128 | 93.54% | ✗ |
| [10] | XGboost | T | 128 | 95% | ✗ |
| [27] | SAE DL | B | 128 | 94.91% | ✗ |
| [22] | NNGE+STEM | M | 128 | 93% | ✗ |
| [21] | CNN | T | 150 | 94% | ✗ |

SAEDL: Stacked-Autoencoder Deep Learning, NNGE+STEM: Non Nested Generalized Exemplars State Extraction Method, CNN : Convolution Neural Network, B : Binary Class, T : Three Class, M : Multi Class, CD : Concept Drift

# Conclusions and Future Direction



This work-in-progress provides three main insights:

- Ability of dynamic retraining of ML based model
- Focus on three class recognition, to include natural events
- Generalize the model for any power grid setup

Future work: We are in process of collecting more data with increased feature set, and we will also consider timestamp and drift based on timing.

# Q&A



**Thank you for your time!**