## BIRD ICRDE: Task 12 –

Israel-U.S. Energy Center (Cyber Topic)



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#### M12.1 An algorithm to minimize false-positive anomalies using explanations

M12.2 An algorithm to identify hidden similarities between instances using explanations

M12.3 Explaining autoencoder's output

## Explainable AI





## **Explainable AI XAI Categories** Explanation Type 🧧

Visual-Feature Importance-Data Point-Surrogate models-









- Additive feature attribution method that is based on game theory and used for understanding why a model makes a certain prediction.
- Assigns each feature an importance value for a particular prediction that represents the marginal contribution of each player in a coalition



<u>https://github.com/slundberg/shap</u>







S-subset of players

 $i-specific\ player$ 

Shap



## From players to models

SHAP Value for feature i, contribution of feature ito model prediction f(x)

Average over all features' subsets  $S \subseteq N/\{i\}$ 

Marginal contribution  $f(S \cup \{i\}) - f(S)$ 





- f-model
- N-all features
- S-subset of features
- $i-specific\ feature$
- x inctance being explained

## Shapley values





https://towardsdatascience.com/shap-shapley-additive-explanations-5a2a271ed9c3

## Shapley values











	mse_all_columns	squared_error_gwk_fremdlohn	squared_error_kilometerstand_km	squared_error_ANZ_FL	squared_error_g
gewaehrleistung_id					
396447471	0.00389	0.00001	0.01188	0.00001	
426290505	0.00328	0.00000	0.02527	0.00000	
397583333	0.00231	0.00000	0.00525	0.00000	
448687344	0.00214	0.00001	0.02209	0.00001	
393807169	0.00198	0.00012	0.00899	0.00012	
446651339	0.00195	0.00001	0.00000	0.00001	
396791336	0.00184	0.00011	0.00142	0.00010	
430558611	0.00180	0.00001	0.01478	0.00001	
450577118	0.00176	0.00000	0.00340	0.00000	
447341408	0.00166	0.00010	0.00001	0.00009	
431233221	0.00162	0.00001	0.01932	0.00001	
389803933	0.00161	0.00006	0.00158	0.00006	
443623241	0.00160	0.00007	0.00000	0.00007	
392789926	0.00151	0.00006	0.01302	0.00006	
447342481	0.00141	0.00000	0.00566	0.00000	









### **ICNL** Data

- Energy production using 3 turbines
- Composed of:
  - sensors readings (every second)
  - network traffic (can be multiple in a second)







## Quick Data overview

Anomaly_Type	Counts	Relative_Percentage
0	87461	88.48
1	5875	5.94
2	5511	5.58

0 = Normal

1 = Operational failures

2 = Cyber Attacks

#### **ICNL** Data

#### Testbed

- Duration of 7 days (8 hours a day)
- Activity recorded: Normal/Operational fault/Cyber attack

#### Normal / Normal + Operational failures / Normal + Operational failures + Cyber Attacks

Day	Date	Recorded	Recorded	PCAP Size (GB)
		Physical(csv)	Network(pcap)	
1	12/06/2023	V	-	-
2	13/06/2023	V	V	7.1
3	14/06/2023	V	V	5.2
4	15/06/2023	V	V	5.4
5	18/06/2023	V	V	3.6
6	19/06/2023	V	V	4.0
7	20/06/2023	-	V	3.5







#### ICNL testbed - Network

- Network Components: HMI, Engineering station, main PLC, secondary PLC, sensors and actuators
- Industrial protocol used: S7comm by siemens
- Majority of functions are read requests, few write requests are present as well
- Aggregated Features(seconds):
  - Protocols- tcp/udp/s7comm/etc..
  - Known IP's (HMI/Eng. Station/PLC's/etc..) as source/destination
  - Unknown IP's as source/destination
  - Read requests
  - Write requests

For each aggregated feature we create sum features for the last 10,30,60,300,1800 seconds.

#### Data



#### **ICNL testbed - Network**



• Write commands sent from the Engineering Station computer may suggest about operational fault or cyber attack



ts

Note: Red background indicates attack interval, Blue indicates operational fault.

#### Data



#### **ICNL testbed - Network**

• Packets sent from an unknown IP source may suggest a potential cyber attack





#### Data



#### **ICNL testbed - Network**



 Number of packets sent from the Engineering Station computer may suggest some of the operational faults



#### ts

### Data

#### **ICNL testbed - Network**

• Number of UDP protocol packets may suggest a potential cyber attack







## Experiments

- Goals
  - To find a connection in the explanations of anomalies revealed by different models
  - Reduce false positive anomalies using the connection between the explanations
- Challenges
  - The quality of the explanations is limited by the quality of the anomaly detector
  - How to make a decision if an event is anomalous or not there are many parameters for the decision (number of explaining features, how many models from the ensemble need to agree with each other)

## Random forest model

- Model parameters:
  - n\_estimators=250
  - Test size = 10%, train size = 90% (split random seed = 42)
- Model evaluation metrics (10-fold stratified cross validation on the train part):
  - Average Accuracy: 0.99
  - Average Precision: 0.9996070343762227
  - Average Recall: 0.9996065685385828
  - Average AUC-ROC (OvO): 0.9999991250210561

# Tsne on the original test set records

# Tsne on shap values explaining the test set



## Autoencoder



- Model training parameters:
  - nb\_epoch=4000
  - batch\_size=30000
  - All the data (98,847 records, normalized)
- Kernel's SHAP explainer parameters:
  - nsamples=500
  - num\_of\_features = 1

## Original records vs. Explanations

shap values tsne

original anomaly data tsne





- Continue analyzing the results
- Add physical data
- Run on another dataset