Domain-Adversarial Transfer Learning for Robust Intrusion Detection in the Smart Grid

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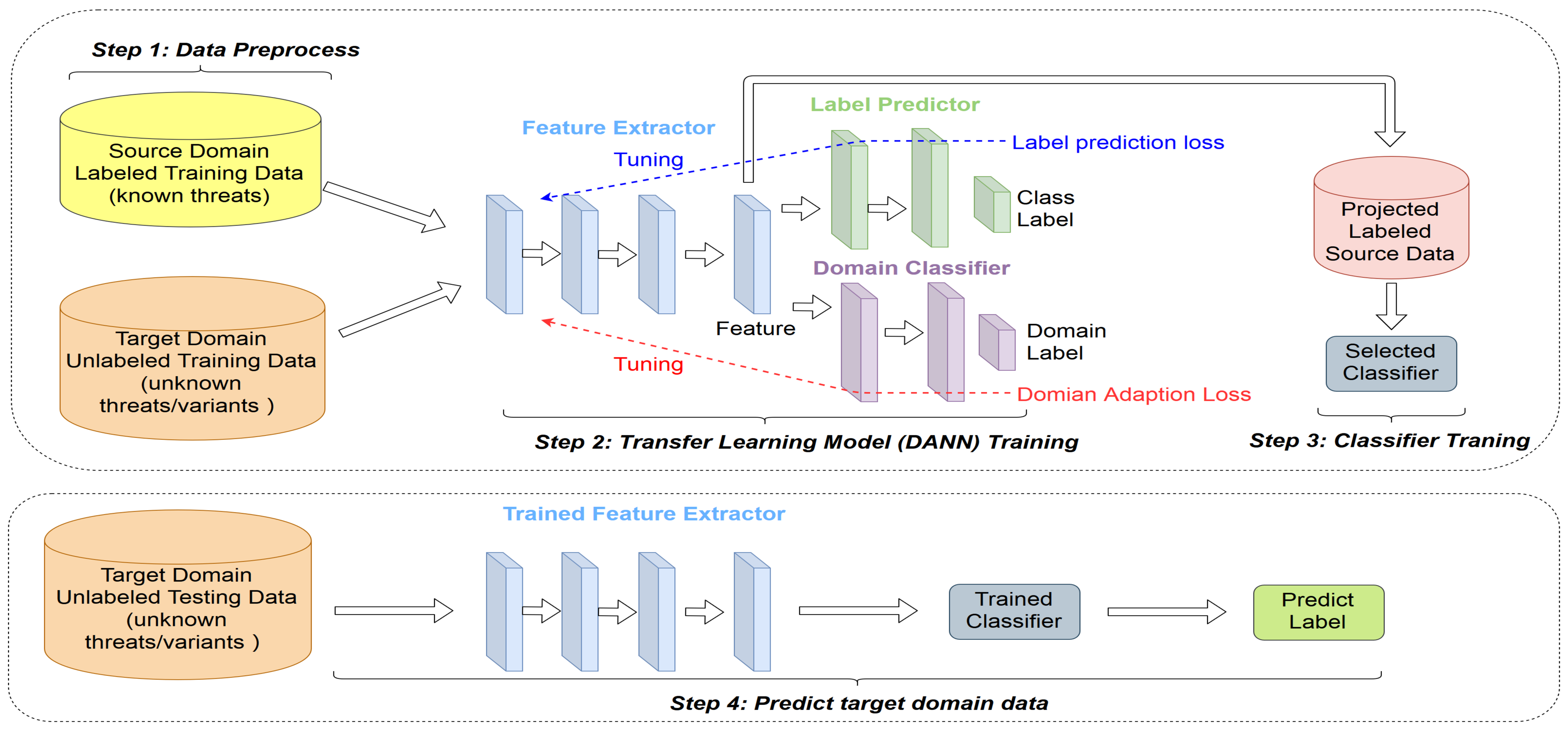
Cyber-Physical Security and Intrusion Detection for the Smart Grid

- Cyber-physical smart grid mainly consists of generation, transmission, distribution systems communicating over a vast network in the cyberspace.
- The smart grid faces growing cyber-physical attack threats aimed at the critical systems and processes communicating over the complex cyber-infrastructure.
- Machine learning (ML)-based detection and classification have been increasingly effective and adopted against sophisticated attacks [1]-[3].
- Limitation of ML-based methods: Classic machine learning methods may not perform well once the data distribution has changed after training.

Domain Adversarial Neural Network for Robust Intrusion Detection

- Domain Adversarial Neural Network [4] is one of the state-of-the-art transfer learning methods, which leverages the adversarial training to help neural network find a mapping of data from two domains into same space with similar distribution. Then we can apply the trained source domain classifier on target domain.
- Overview of the DANN based framework:



- Objective Function:

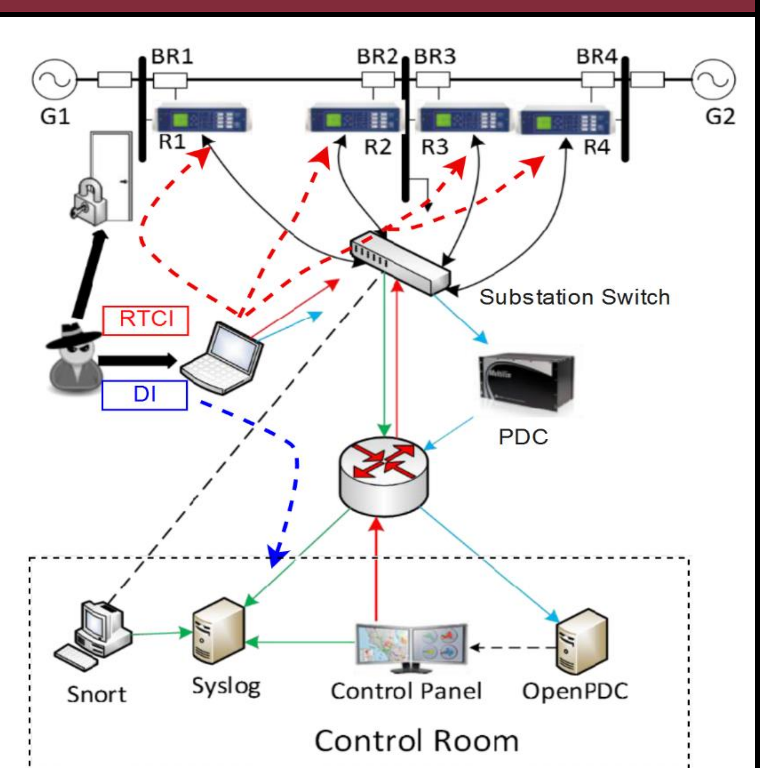
$$\min_{\mathbf{W},\mathbf{b},\mathbf{V},\mathbf{c}} \left[\frac{1}{n_S} \sum_{\mathbf{x} \in \mathcal{D}_S} L_y(\mathbf{x}, y) + \lambda \cdot R(\mathbf{W}, \mathbf{b}) \right]$$

Combining the losses of event misclassification and domain separation.

Dataset

- The Dataset is from a hardware-in-the-loop testbed by University of Alabama in Huntsville and the Oak Ridge National Lab (ORNL) [5], [6].

Classes	Scenarios	Descriptions
Normal	No Events	Normal operation with load variation
Attack	Data Injection (DI)	Attacker manipulates current, voltage, etc. to mislead controllers and/or operators into mal-operations.
	Remote Tripping Command Injection (RTCI)	Attacker sends a command to a relay and open a circuit breaker, directly causing a line outage.



Experiments Description

- We create several cases where there is unseen attack in testing set or same attack with different locations.

Cases	Threat in Source Domain	Threat(s) in Target Domain	Transfer Between
1	DI	RTCI	Different types of attack (measurement to command)
2	DI	DI and RTCI	
3	RTCI	DI	Different types of attack (command to measurement)
4	RTCI	DI and RTCI	
5	RTCI-15 (RelayR1)	RTCI-16 (RelayR2)	Different location of same attack
6	RTCI-17 (Relay R3)	RTCI-18 (Relay R4)	

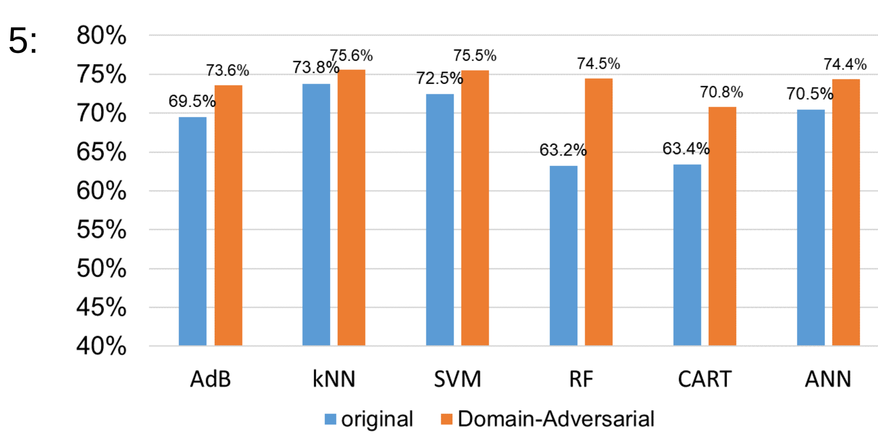
Classification Performance

- Transfer to new attacks:

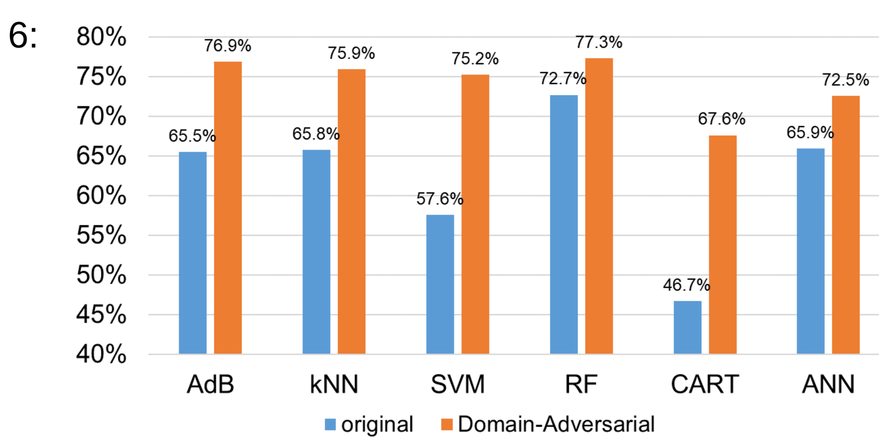
Cases	Methods	AdaBoost	kNN	SVM	Random Forest	CART	ANN
1	Original	72.0%	77.6%	57.9%	51.4%	53.2%	83.0%
	Domain-Adversarial	86.8%	86.0%	82.9%	88.2%	76.3%	84.5%
	Improvement	**+ 14.8%**	**+ 8.5%**	**+ 25.0%**	**+ 36.8%**	**+ 23.1%**	**+ 1.5%**
2	Original	77.3%	82.7%	71.0%	84.5%	76.7%	86.5%
	Domain-Adversarial	94.2%	90.4%	85.5%	95.2%	79.2%	87.8%
	Improvement	**+ 16.9%**	**+ 7.8%**	**+ 14.5%**	**+ 10.7%**	**+ 2.5%**	**+ 1.3%**
3	Original	73.0%	75.1%	64.8%	76.0%	61.3%	81.7%
	Domain-Adversarial	83.6%	82.2%	80.9%	84.5%	75.7%	83.6%
	Improvement	**+ 10.6%**	**+ 7.1%**	**+ 16.1%**	**+ 8.5%**	**+ 14.4%**	**+ 1.9%**
4	Original	71.2%	80.5%	66.7%	83.0%	69.5%	85.9%
	Domain-Adversarial	89.3%	88.2%	85.3%	90.0%	79.6%	87.6%
	Improvement	**+ 18.1%**	**+ 7.7%**	**+ 18.6%**	**+ 7.0%**	**+ 10.1%**	**+ 1.6%**

- Transfer to different locations:

Case 5:



Case 6:



Conclusions

- All baseline classifiers can benefit significantly from the domain-adversarial training and demonstrate robust performance against unseen types and different locations of threats.
- For future work we will extend the knowledge transfer ability among:
  - *Events*, e.g. normal operations, planned maintenance, system faults, extreme weather damage, and intentional attacks;
  - *Scenarios*, e.g., heterogeneous manufacturers, protocols, standards, topologies, and wired/ wireless configurations.
- References:

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