Steerable Deep Transfer Learning for Critical Infrastructure Attack Detection

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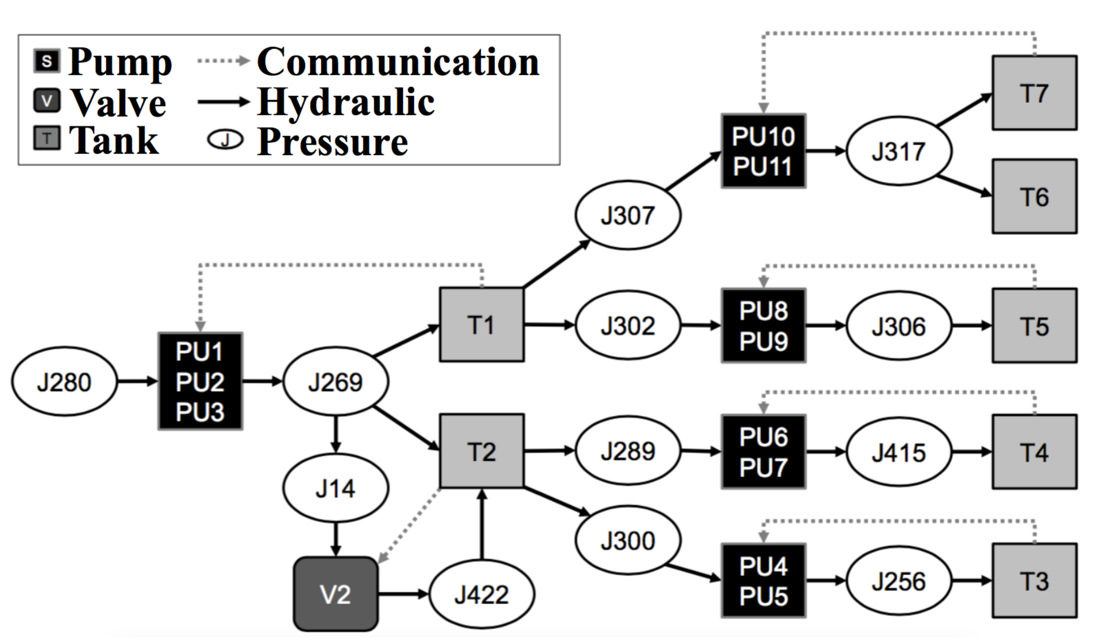
Problem

- **Motivation:** Computers regulate modern water distribution, increasing likelihood of cyber attacks [1].
- **Approach:** We use deep learning to flag cyber attacks in sensor data from water distribution systems.
- **Competition:** Recent literature favors unsupervised deep learning, which characterizes attacks as anomalous occurrences in clean sensor data.
- **Contribution:** We contribute a *steerable* transfer learning model that trains a deep neural network on customizable synthetic attacks.
- **Justification:** Our model gives the driver more agency in the attack detection process.
- **Benefit:** Success of our model and transition to deployment informs safe water distribution.

Data

- Raw data are 8761 hourly, simulated readings from 43 sensors in a real water distribution system [2].
- We remove 7 negligible-variance features, scale each feature within $[0, 1]$, and roll the data into windows.
- Hierarchy of water distribution system's hydraulic components shown below [3].

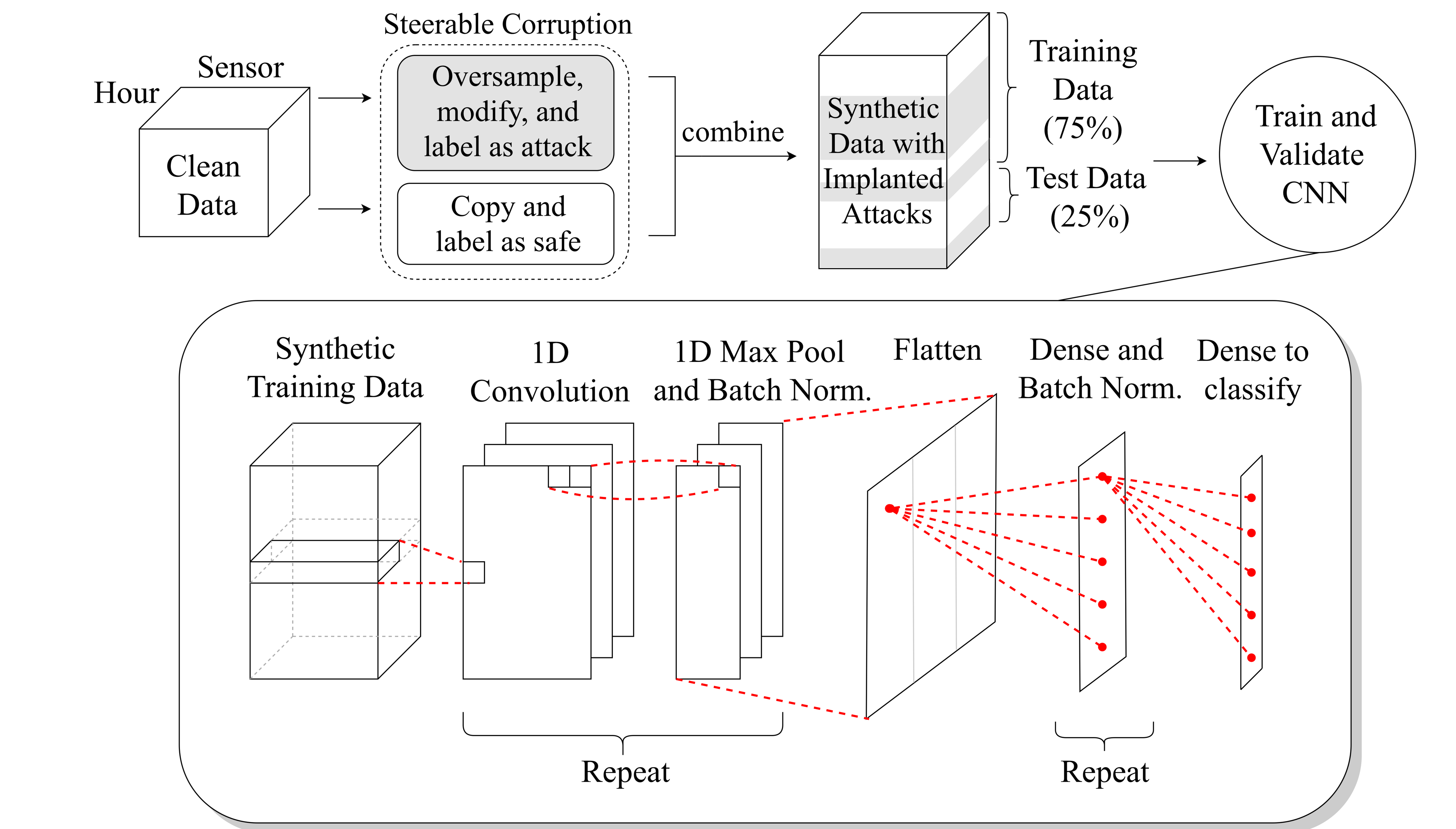


Attack data. We generate synthetic data as follows:

- Oversample clean windows and modify each observation with one attack by swapping random contiguous sub-ranges of 2 sensors' readings.
- Include one unmodified copy of pre-processed data for examples of safe observations.

Model

- We coded the convolutional neural network (CNN) in SciPy [4], Keras [5], and TensorFlow [6].
- Convolutional layers learn temporal patterns and dense layers recognize global relationships.
- Other layers regularize parameters, prevent over-fitting, and reduce computational intensiveness.



Results

Domain-agnostic model detects synthetic attacks?

Predicted Class \ True Class	ATTACK	SAFE
ATTACK	0.99	0.11
SAFE	0.01	0.89

Domain-agnostic synthetic test set

Domain-agnostic model detects real attacks?

Predicted Class \ True Class	ATTACK	SAFE
ATTACK	0.97	0.79
SAFE	0.03	0.21

Realistic test set [2]

Domain-specific model detects real attacks?

Predicted Class \ True Class	ATTACK	SAFE
ATTACK	0.94	0.36
SAFE	0.06	0.64

Realistic test set [2]

Iterative model detects real attacks?

Predicted Class \ True Class	ATTACK	SAFE
ATTACK	0.39	0.03
SAFE	0.61	0.97

Realistic test set [2]

- **Best model:** 3 convolutional layers with 10 filters of length 5 and 2 dense layers of dimension 30.
- Networks with highest test accuracy had many convolutional layers with few filters (144 tests).
- Model classifies synthetic attacks with 95% accuracy and realistic attacks [2] with high recall.
- Domain-specific ablation: swapping only among like sensors reduces false positives.
- By training on domain-specific synthetic data, and then a realistic training set [2], false positives diminish to negligible levels at expense of false negatives. **Results are more accurate than training on realistic training set alone** (confusion matrix not shown).

Conclusions

- Our model accurately classifies implanted attacks.
- Domain-agnostic and domain-specific models have high recall.
- False positives drastically decrease with only one simple domain-specific assumption.
- Iterative training with synthetic and realistic attack data reduces overfitting and suppresses alarms at the expense of false negatives.
- Naïve steering has potential to facilitate customizable attack detection.

Next steps.

- Perform more extensive ablation study.
- Characterize synthetic attacks that steer model toward detecting specific real attacks.
- Replicate results with datasets from other domains.

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References

[1] Hill, M. "Water Treatment Plant Hit by Cyber-attack." *Infosecurity Magazine,* March 2016.

[2] Taormina, R. *et al.* The Battle Of The Attack Detection Algorithms: Disclosing Cyber Attacks on Water Distribution Networks. *Jnl. of Water Resources Planning and Mgmt.*, 2018.

[3] Chandy, S. *et al.*, Cyberattack detection using deep generative models with variational inference, *Jnl. Water Resources Planning and Mgmt.*, 2018.

[4] Jones E. *et al.* SciPy: Open Source Scientific Tools for Python, 2001. `https://www.scipy.org/`.

[5] Chollet, F. *et al.* Keras, 2015. `https://keras.io`

[6] Abadi, M. *et al.* TensorFlow: Large-scale ML on heterogeneous systems, 2015. `https://tensorflow.org`

[7] Ioffe, S. and C.Szegedy, Batch normalization: Accelerating deep network training by reducing internal covariate shift, CoRR, vol. abs/1502.03167, 2015.

Steerable Deep Learning for Critical Infrastructure Attack Detection

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Central control systems automatically regulate water distribution networks based on hydraulic sensor readings. Adversaries can hack this emergent cyber layer to alter readings and disrupt safe water distribution. We furnish a flexible model that uses transfer learning and customizable data augmentation to detect attacks. We augment clean sensor data with domain-agnostic "attacks", with which we train a 1D-convolutional neural network. Our model detects real attacks with high recall and a high false positive rate. By making one simple domain-specific assumption on synthetic attacks, we drastically reduce false positives by more than half with minimal sacrifice. When training on real attacks, a warm start on domain-specific synthetic attacks yields higher accuracy than no warm start. Our work supports naïve steering as a new attack detection paradigm. Success and transition to deployment would inform national water infrastructure security.