

# High-Performance Unsupervised Anomaly Detection for Cyber-Physical System Networks

Peter Schneider, Konstantin Böttinger, October 19, 2018 / CPS-SPC

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The logo for IUNO, consisting of the letters "IUNO" in a stylized, rounded font. The "I" is blue, "U" is teal, "N" is green, and "O" is light green.

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Nationales Referenzprojekt  
IT-Sicherheit in Industrie 4.0

# Anomaly Detection for CPS Networks

## Intro

**Who** *Peter Schneider*, Konstantin Böttinger

**What** Anomaly Detection

**When** Online Detection

**Where** Cyber-Physical System Networks

**Why** High-Performance, Unsupervised

**How** Stacked Denoising Autoencoders

**For what** Detection in proprietary and/or binary protocols

# Anomaly Detection for CPS Networks

## Motivation

- Rising number of attacks on cyber-physical systems (CPS)
- 100%-secure systems are impossible
- Network-based Anomaly Detection widely suggested as solution

# Anomaly Detection for CPS Networks

## The Problem

- Detection systems for business IT already available
- Adaptation of systems to CPS domain still ongoing
- Including domain-specific knowledge should increase detection capabilities

# Anomaly Detection for CPS Networks

## What happens now



Figure: Insecure manufacturing system.

# Anomaly Detection for CPS Networks

## What happens now



Figure: Secure manufacturing system.

# Anomaly Detection for CPS Networks

## Challenges

- slow updates
- long product lifetime
- once protected environments
- high damage potential
- specialized attacks
- binary/proprietary protocols

# Anomaly Detection for CPS Networks

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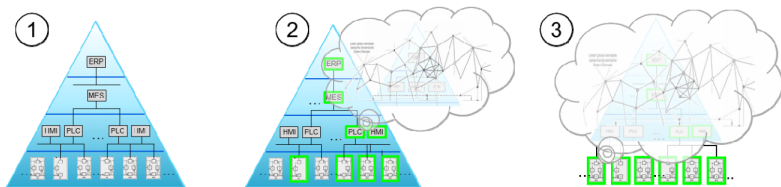


Figure: VDI, Cyber-Physical Systems: Chancen und Nutzen aus Sicht der Automation



# Anomaly Detection for CPS Networks

## How it is usually done

data acquisition phase



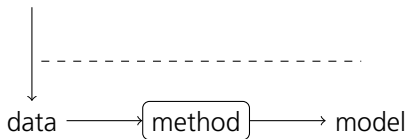
data

# Anomaly Detection for CPS Networks

## How it is usually done

data acquisition phase

learning phase



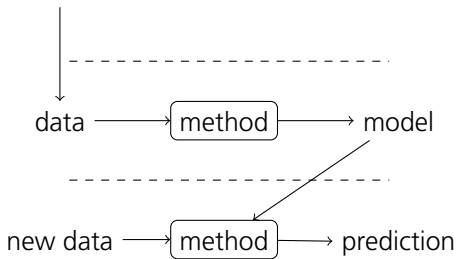
# Anomaly Detection for CPS Networks

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learning phase

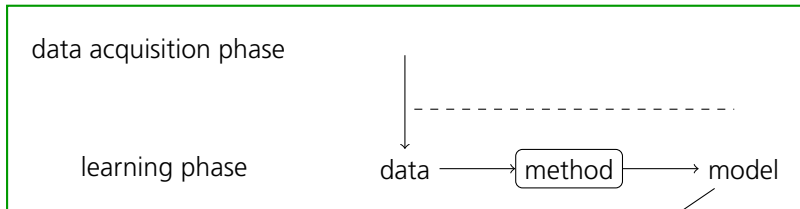
detection phase



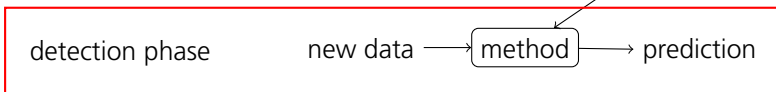
# Anomaly Detection for CPS Networks

## How it is usually done

### Offline



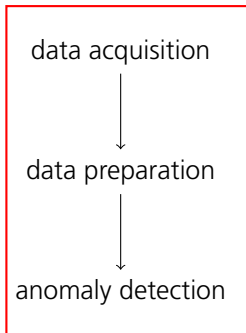
### Online



# Anomaly Detection for CPS Networks

## How it (not) works

Online



# Anomaly Detection for CPS Networks

## Performance

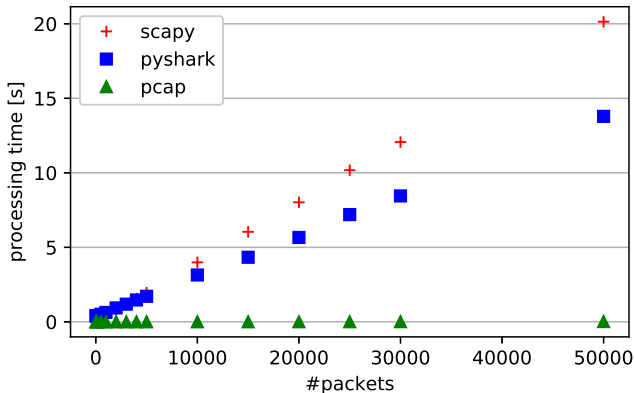


Figure: Performance comparison using different data aggregation strategies.

# Anomaly Detection for CPS Networks

## Performance

# packets	scapy	pyshark	pcap
1000	0.38s	0.63s	< 0.01s
3000	1.17s	1.19s	< 0.01s
10000	3.99s	3.15s	< 0.01s
50000	20.14s	13.79s	0.02s

# Anomaly Detection for CPS Networks

## Performance

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**Assumptions** bandwidth: **100Mbit/s**, average packet length: **100bytes**

**Result** up to **131072** network packets per second



# Anomaly Detection for CPS Networks

## Observations

- packet parsing infeasible for larger CPS networks
- classic ML feature extraction not possible

We need a faster solution for **feature extraction** and **anomaly detection!**

# Anomaly Detection for CPS Networks

## Pipeline

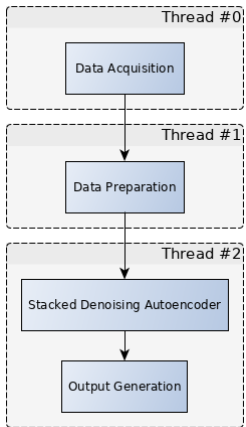


Figure: High-Performance Pipeline

# Anomaly Detection for CPS Networks

## Pipeline

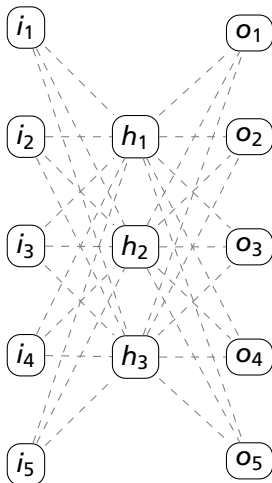
data acquisition real-time capturing

data preparation length cut-off or padding

anomaly detection stacked denoising autoencoders

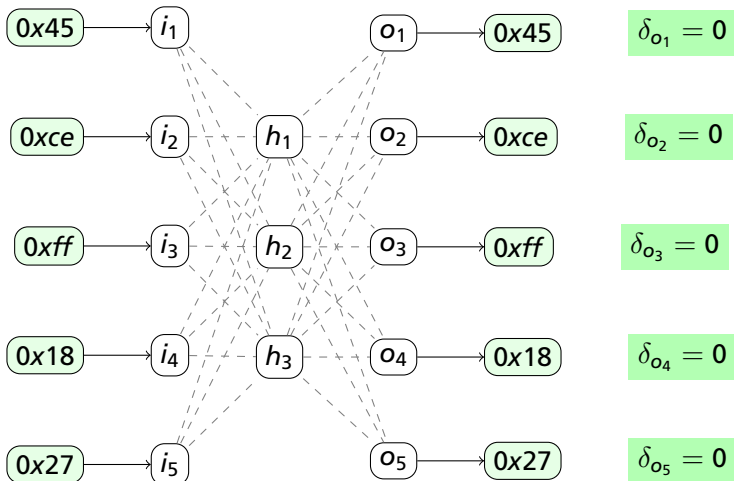
# Anomaly Detection for CPS Networks

## Autoencoder-based Detection



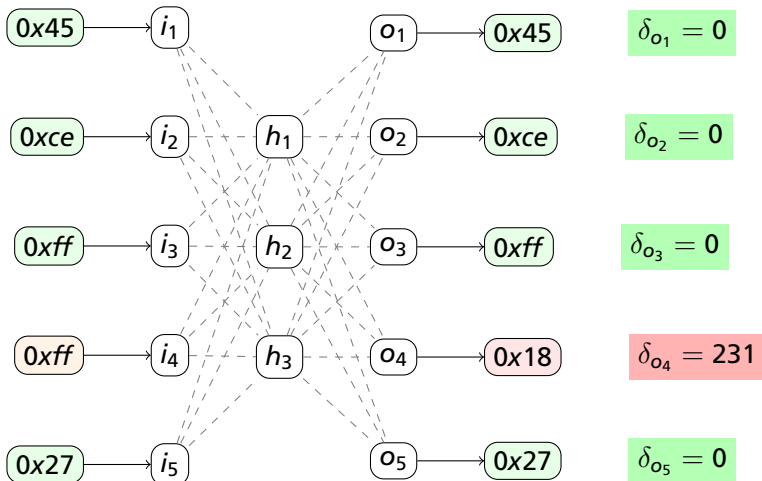
# Anomaly Detection for CPS Networks

## Autoencoder-based Detection



# Anomaly Detection for CPS Networks

## Autoencoder-based Detection



# Anomaly Detection for CPS Networks

## SDA

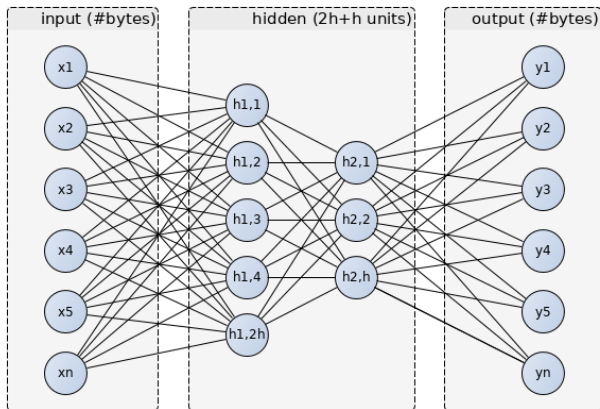


Figure: Stacked auto-encoders.

# Anomaly Detection for CPS Networks

## Experiments

### Modbus dataset

- labeled network packets
- several traces with and without attacks

### SWaT dataset

- large dataset (~500GB)
- traces from several days with and without attacks
- pcap traces not labeled



# Anomaly Detection for CPS Networks

## Modbus dataset – training data

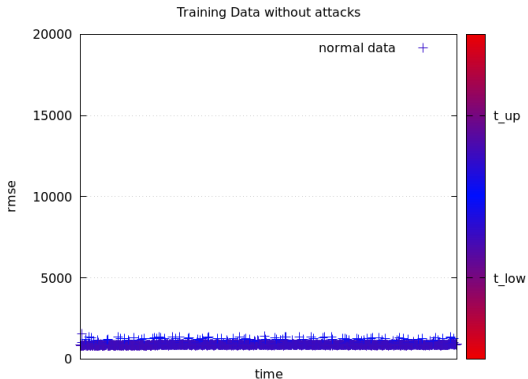


Figure: RMSE on the run1\_3rtu\_2s trace.

# Anomaly Detection for CPS Networks

## Modbus dataset – validation data

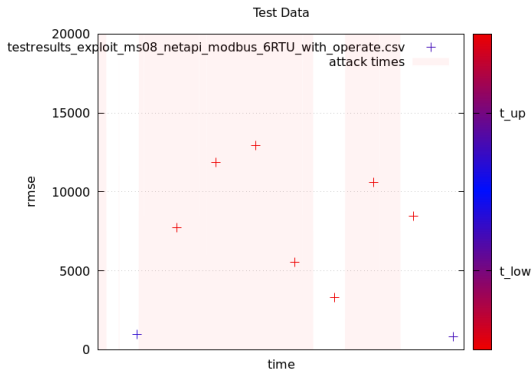


Figure: RMSE on the exploit\_ms08\_netapi\_modbus\_6RTU\_with\_operate trace.

# Anomaly Detection for CPS Networks

## Modbus dataset – validation data

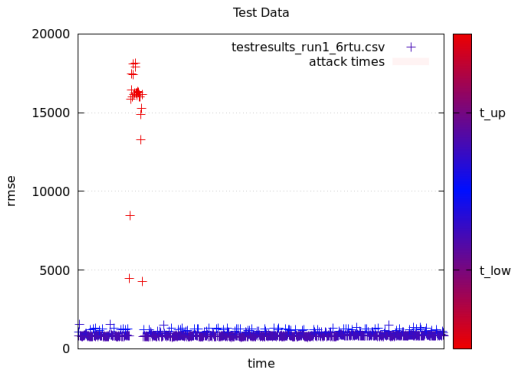


Figure: RMSE on the run1\_6rtu trace.

# Anomaly Detection for CPS Networks

## SWaT dataset

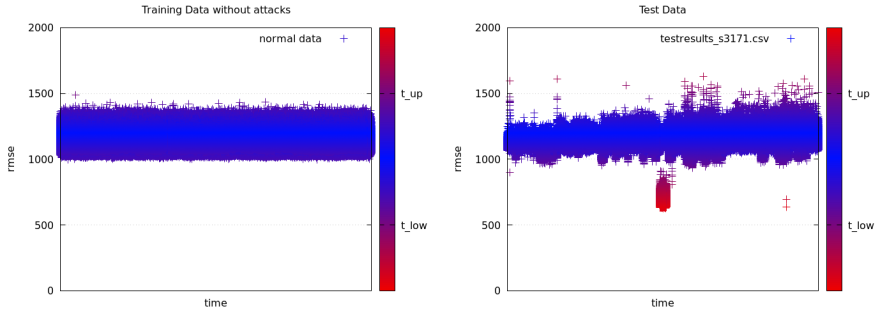
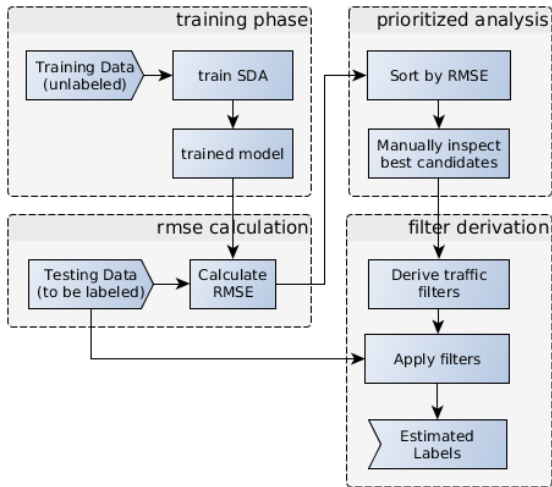


Figure: Results on SWaT dataset.

# Anomaly Detection for CPS Networks

## Label Estimation



# Anomaly Detection for CPS Networks

## Labels Estimated

**dupack** duplicated acknowledgements  
*tcp.analysis.duplicate\_ack*

**retransmit** retransmitted packets  
*tcp.analysis.retransmission* or *tcp.analysis.fast\_retransmission*

**unknownproto-tls** newly introduced TLS layers  
*manual analysis*

**tcpreset** connection resets using TCP RST flag  
*tcp.flags.reset==1*

**synflood** flooding using TCP SYN packets  
*transum.status=="Response missing"* and *tcp.connection.syn*

# Anomaly Detection for CPS Networks

## SWaT dataset, detailed results

Line		dupack	retransmit	unknownproto-tls
1	precision	6.38%	2.22%	4.35%
2	recall	3.95%	1.00%	0.38%
3	f1	4.88%	1.38%	0.70%

Table: Anomaly detection performance in problematic scenarios.

# Anomaly Detection for CPS Networks

## SWaT dataset, detailed results

Line		tcpreset	synflood
1	precision	99.80%	99.80%
2	recall	99.77%	99.99%
3	f1	99.78%	99.89%

Table: Anomaly detection performance in well-working scenarios.

Naive classifier Using packet length → 0% f1-score



# Anomaly Detection for CPS Networks

## Conclusion

Where Cyber-Physical System Networks  
→ **SWaT** (EtherNet/IP) and **Modbus** datasets for validation

# Anomaly Detection for CPS Networks

## Conclusion

- Where** Cyber-Physical System Networks  
→ **SWaT** (EtherNet/IP) and **Modbus** datasets for validation
- Why** High-Performance  
→ fast **data acquisition** omitting packet parsing  
Unsupervised  
→ **feature learning** using SDAs

# Anomaly Detection for CPS Networks

## Conclusion

**Where** Cyber-Physical System Networks

→ **SWaT** (EtherNet/IP) and **Modbus** datasets for validation

**Why** High-Performance

→ fast **data acquisition** omitting packet parsing

Unsupervised

→ **feature learning** using SDAs

**For what** Detection in proprietary and/or binary protocols

→ up to **99%** f1-scores

# Contact Information



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