A Deep Neural Network for Unsupervised Anomaly Detection and Diagnosis in Multivariate Time Series

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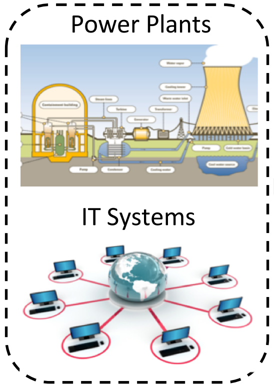
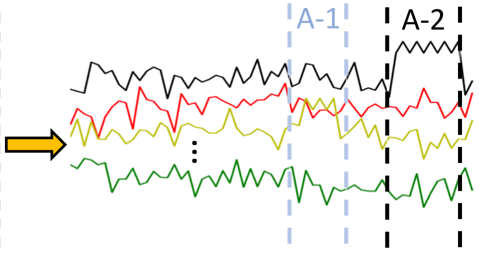
Motivation & Goal

- Large Scale Complex Systems/Multivariate Time Series





- Normal period: little/no label
- few root causes
- multi-scale (duration) anomalies

Goal

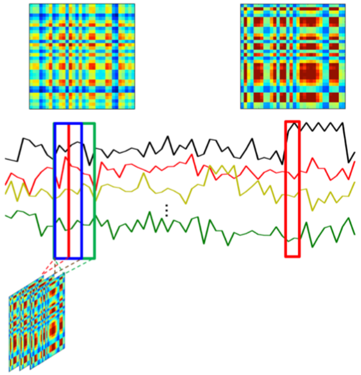
- Unsupervised Anomaly Detection: A_1, A_2
- Anomaly Diagnosis
  - ✓ Root cause identification: find causal sensor
  - ✓ Anomaly scale analysis: interpret anomaly duration

Challenges

- C1: Time series contain noise
- C2: Multi-dimensional input, Temporal dependency
- C3: Multi-scale (duration) anomalies

Model

- System Signature for C1 (avoid noise)
  - Signature matrix: compute inner-product between every pair of sensors on each time segment
  - Capture both shape and range
  - Robust to noise as the noise of individual time series impacts little on the signature of the whole system
- Auto-Encoder for C2 (multi-dimen, temporal)
  - Signature matrix pattern encoding: CNN
  - Temporal dependency modeling: RNN
  - Signature matrix pattern decoding: CNN
  - Profiling the normal period for model training, test the abnormal period
- Multi-Scale Matrices for C3 (multi-scale)
  - Multi-scale (resolution) signature matrices



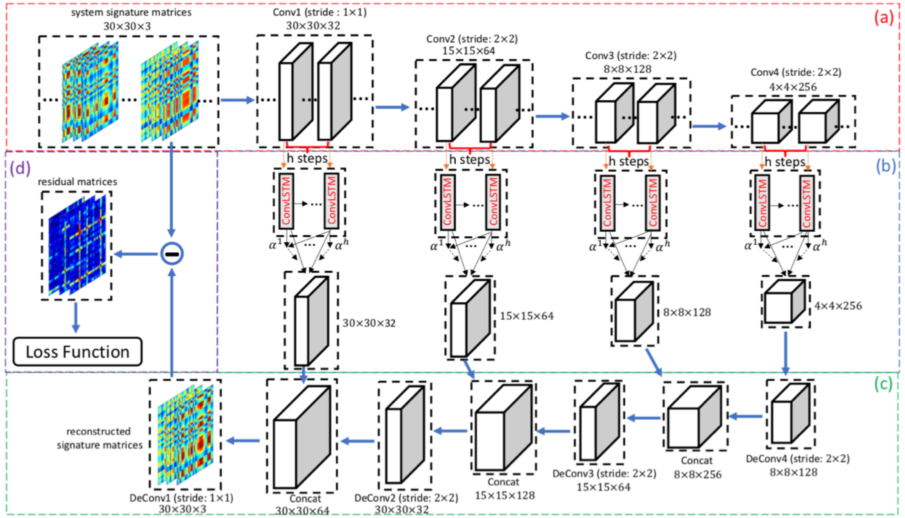


Figure 2: Framework of the proposed model: (a) Signature matrices encoding via fully convolutional neural networks. (b) Temporal patterns modeling by attention based convolutional LSTM networks. (c) Signature matrices decoding via deconvolutional neural networks. (d) Loss function.

Experiment

- Anomaly Detection: Performance

Table 2: Anomaly detection results on two datasets.

Method	Synthetic Data			Power Plant Data		
	Pre	Rec	F_1	Pre	Rec	F_1
OC-SVM	0.14	0.44	0.22	0.11	0.28	0.16
DAGMM	0.33	0.20	0.25	0.26	0.20	0.23
HA	0.71	0.52	0.60	0.48	0.52	0.50
ARMA	0.91	0.52	0.66	0.58	0.60	0.59
LSTM-ED	1.00	0.56	0.72	0.75	0.68	0.71
$CNN^{ED(4)}_{ConvLSTM}$	0.37	0.24	0.29	0.67	0.56	0.61
$CNN^{ED(3,4)}_{ConvLSTM}$	0.63	0.56	0.59	0.80	0.72	0.76
$CNN^{ED}_{ConvLSTM}$	0.80	0.76	0.78	0.85	0.72	0.78
MSCRED	**1.00**	**0.80**	**0.89**	**0.85**	**0.80**	**0.82**
Gain (%)	–	30.0	23.8	13.3	19.4	15.5

- Anomaly Diagnosis: Performance
  - ✓ Root Cause Identification

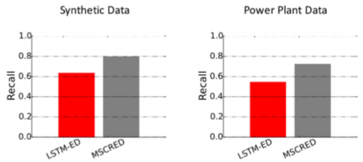


Figure 5: Performance of root cause identification.

  - ✓ Anomaly Scale Analysis

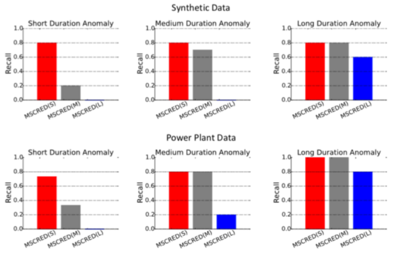


Figure 6: Performance of three channel anomaly scores of MSCRED over different types of anomalies.