An Attention-Based ConvLSTM Autoencoder with Dynamic Thresholding for Unsupervised Anomaly Detection in Multivariate Time Series

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이정민

Paper

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❖ An Attention-Based ConvLSTM Autoencoder with Dynamic Thresholding for Unsupervised Anomaly Detection in Multivariate Time Series

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Article

An Attention-Based ConvLSTM Autoencoder with Dynamic Thresholding for Unsupervised Anomaly Detection in Multivariate Time Series

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Abstract: As a substantial amount of multivariate time series data is being produced by the complex systems in smart manufacturing (SM), improved anomaly detection frameworks are needed to reduce the operational risks and the monitoring burden placed on the system operators. However, building such frameworks is challenging, as a sufficiently large amount of defective training data is often not available and frameworks are required to capture both the temporal and contextual dependencies across different time steps while being robust to noise. In this paper, we propose an unsupervised Attention-Based Convolutional Long Short-Term Memory (ConvLSTM) Autoencoder with Dynamic Thresholding (ACLAE-DT) framework for anomaly detection and diagnosis in multivariate time series. The framework starts by pre-processing and enriching the data, before constructing feature images to characterize the system statuses across different time steps by capturing the inter-correlations between pairs of time series. Afterwards, the constructed feature images are fed into an attention-based ConvLSTM autoencoder, which aims to encode the constructed feature images and capture the temporal behavior, followed by decoding the compressed knowledge representation to reconstruct the feature images' input. The reconstruction errors are then computed and subjected to a statistical-based, dynamic thresholding mechanism to detect and diagnose the anomalies. Evaluation results conducted on real-life manufacturing data demonstrate the performance strengths of the proposed approach over state-of-the-art methods under different experimental settings.

Keywords: anomaly detection; deep learning; unsupervised learning; Industrial Internet of Things; time series

check for updates

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등장 배경

❖ 기존 연구들의 한계

- Time step 길이가 다른 다변량 시계열에서 **Temporal / Contextual** 정보를 담을 수 없음
- 어떤 채널로 인한 이상 시점인지 파악하기 어려움

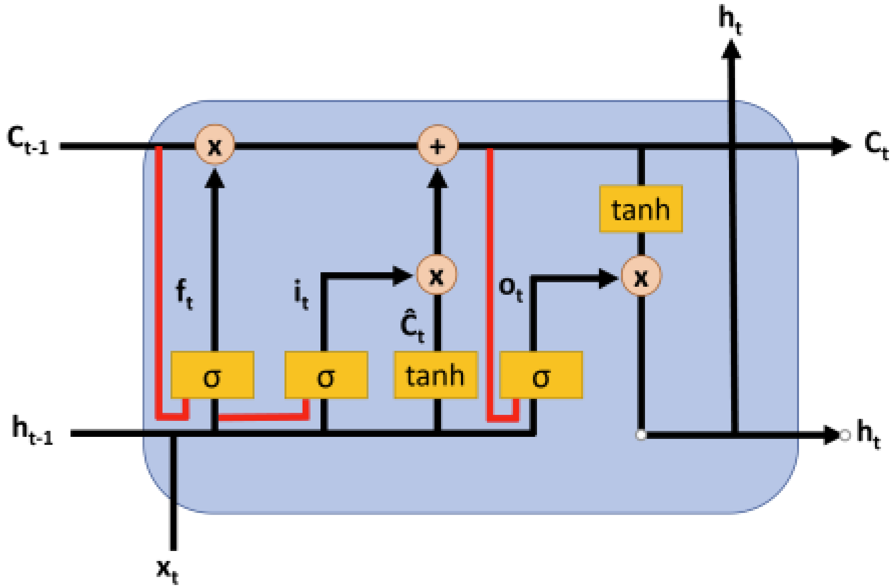
❖ 기여점

- Smart factory에서 다양한 길이의 다변량 시계열 데이터셋에 적용 가능
- 입력 sequence의 길이가 증가해도 성능 유지 가능
- 데이터셋의 비정상성, noise, 다양성 문제를 해결할 수 있는 nonparametric / dynamic thresholding

Base Model

❖ ConvLSTM

- ° : Hadamard product / * : Convolutional operator
- ACLAE-DT : **A**ttention-based **C**onv**L**STM **A**uto**E**ncoder with **D**ynamic **T**hresholding



$$i_t = \sigma(W_{Ci} \circ C_{t-1} + W_{hi} * h_{t-1} + W_{xi} * x_t + b_i)$$
$$f_t = \sigma(W_{Cf} \circ C_{t-1} + W_{hf} * h_{t-1} + W_{xf} * x_t + b_f)$$
$$o_t = \sigma(W_{Co} \circ C_t + W_{ho} * h_{t-1} + W_{xo} * x_t + b_o)$$
$$\tilde{C}_t = tanh(W_{hC} * h_{t-1} + W_{xC} * x_t + b_C)$$
$$C_t = f_t \circ C_{t-1} + (1 - f_t) \circ \tilde{C}_t$$
$$h_t = o_t \circ tanh(C_t)$$

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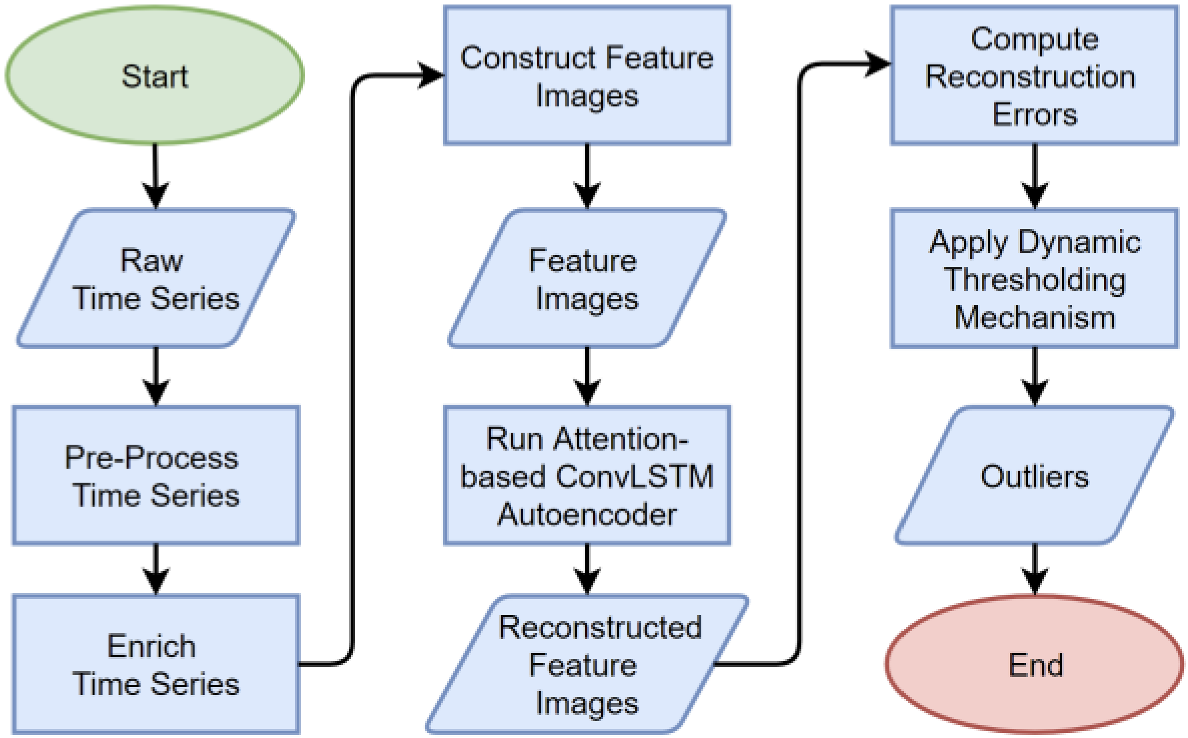
❖ Framework



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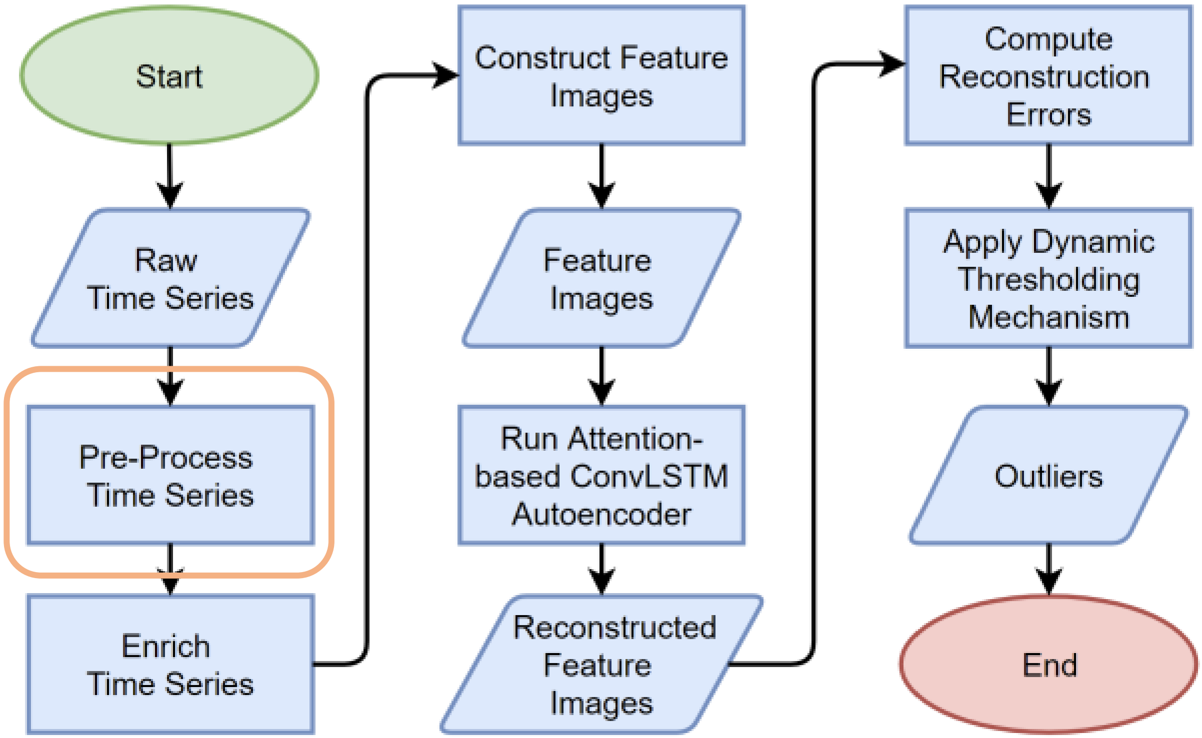
❖ Framework - Preprocessing

Minmaxscaler



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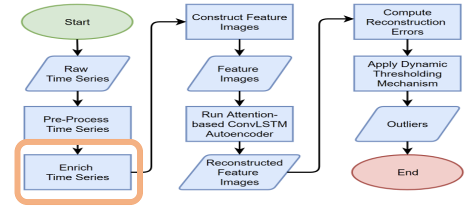
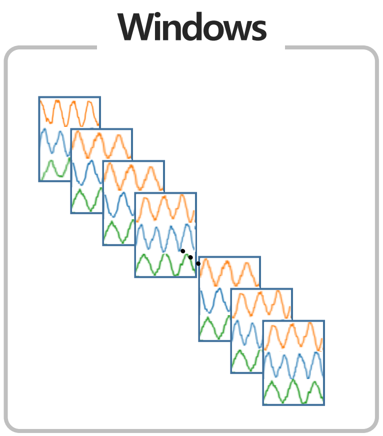
❖ Framework – Enrich Time Series



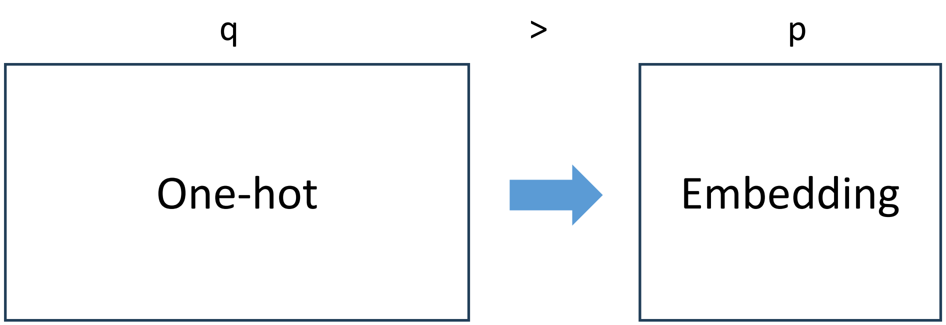
- 수치형 변수: Sliding window
- 범주형 변수: Entity embedding
  - ✓ 기존 one-hot encoding은 category가 많을 경우 비효율적인 연산 야기

[수치형 변수]



Sliding window

[범주형 변수]



Entity embedding

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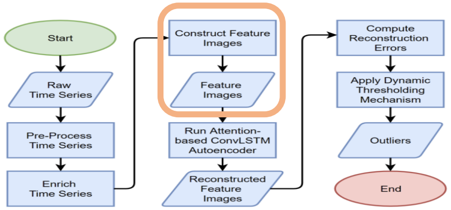
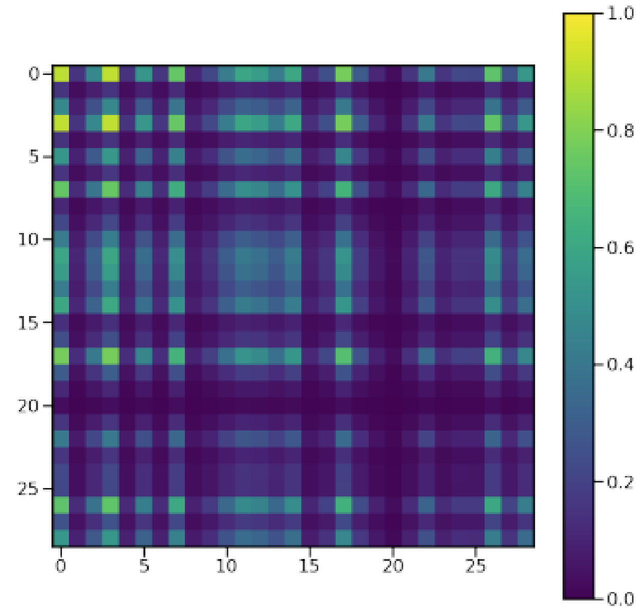


❖ Framework – Construct Feature Images

- $M^t: (n+p) \times (n+p)$
- $m_{ij}^t: inter\ correlation\ between\ time\ series\ i, j$
- $s: each\ segment$

$$m_{ij}^t = \frac{\sum_{\delta=0}^{w} x_i^{t-\delta} x_j^{t-\delta}}{s} \in M^t$$



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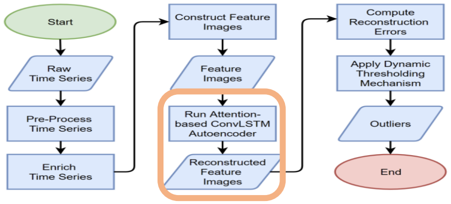
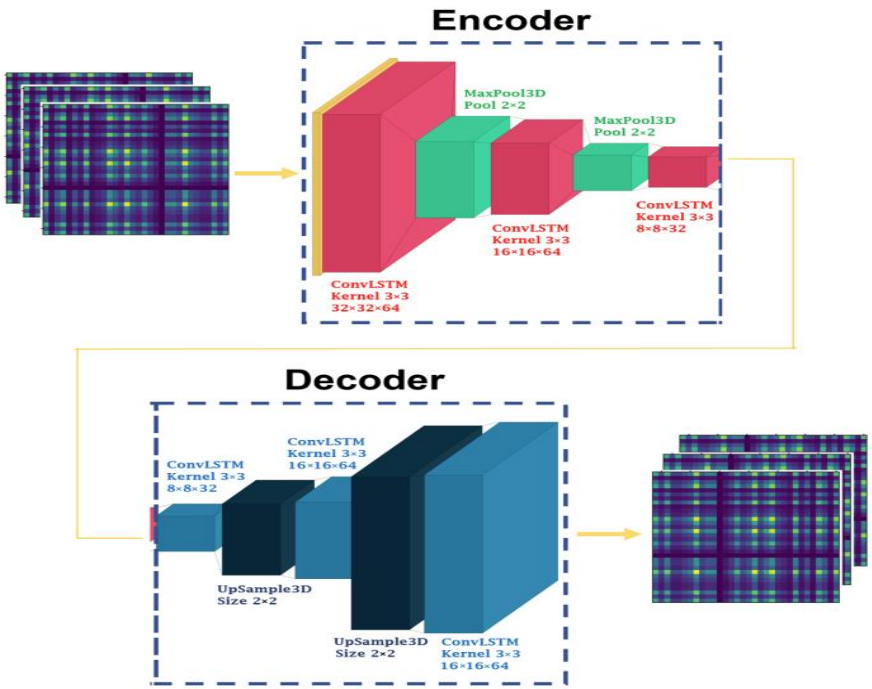
❖ Framework – ACLAE

- Bahdanau attention 사용
  - ✓ Sequence length가 길어질 때 성능 저하를 막기 위함





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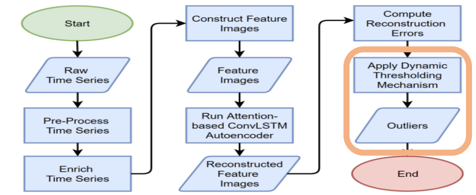
❖ Framework – Dynamic Thresholding

- 각 time series마다 threshold를 다르게 설정 – dynamic
- 한 time step에서 최소 하나의 time series pair가 threshold를 넘으면 해당 time step을 이상 시점으로 판단



정상 구간 reconstruction error matrix

Threshold matrix (n+p)x(n+p)

$$\boxed{\epsilon_{ij}} = \left(\mu\left(\boxed{e_{ij}}\right) + z\sigma(e_{ij})\right)^T \in \epsilon$$

$2 \leq z \leq 5$

0.14	0.07	0.02	0.11
0.04	0.21	**0.34**	0.09
0.03	0.13	0.18	0.08
0.06	0.15	0.11	0.12

[Reconstruction error matrix]

0.16	0.15	0.15	0.14
0.04	0.22	**0.26**	0.17
0.11	0.16	0.2	0.18
0.12	0.19	0.21	0.19

[Threshold matrix]

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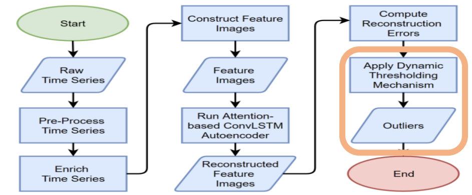

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