Time-Series Data Augmentation for Deep Learning: A Survey

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Purpose of the presentation:
A brief overview on the existing data augmentation techniques for time-series data.

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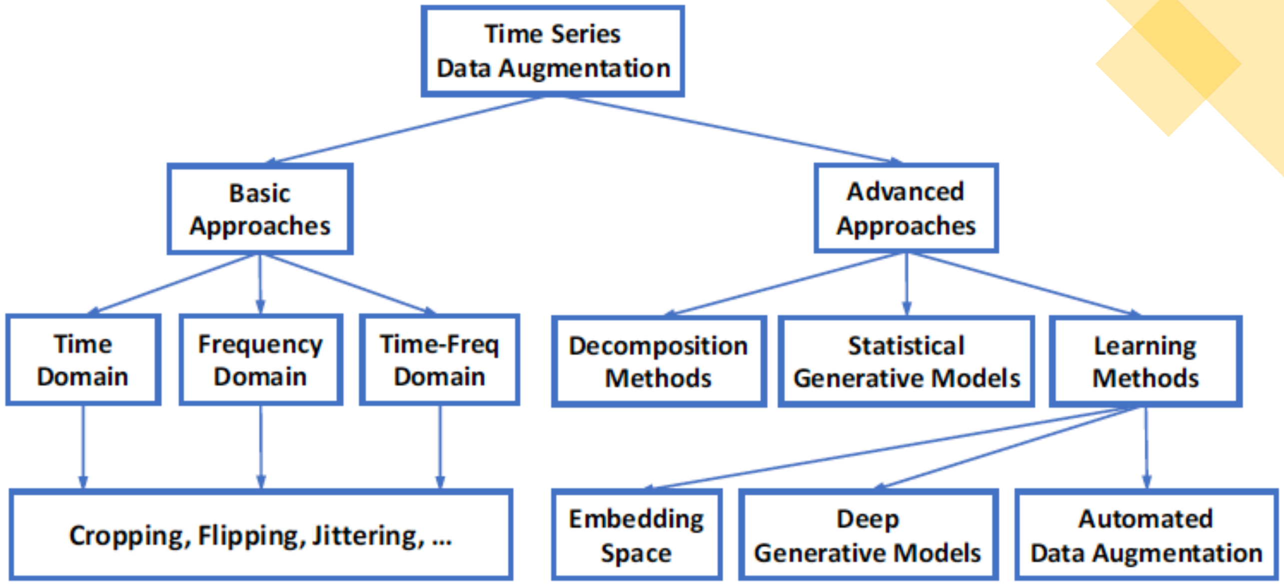
Why Augmentation?

- “The success of deep learning relies heavily on a large size of training data to avoid overfitting.”
- “Unfortunately, many time series tasks do not have enough labeled data.”
- “The labeled data of many real-world time series applications may be limited such as classification in medical time series and anomaly detection.”



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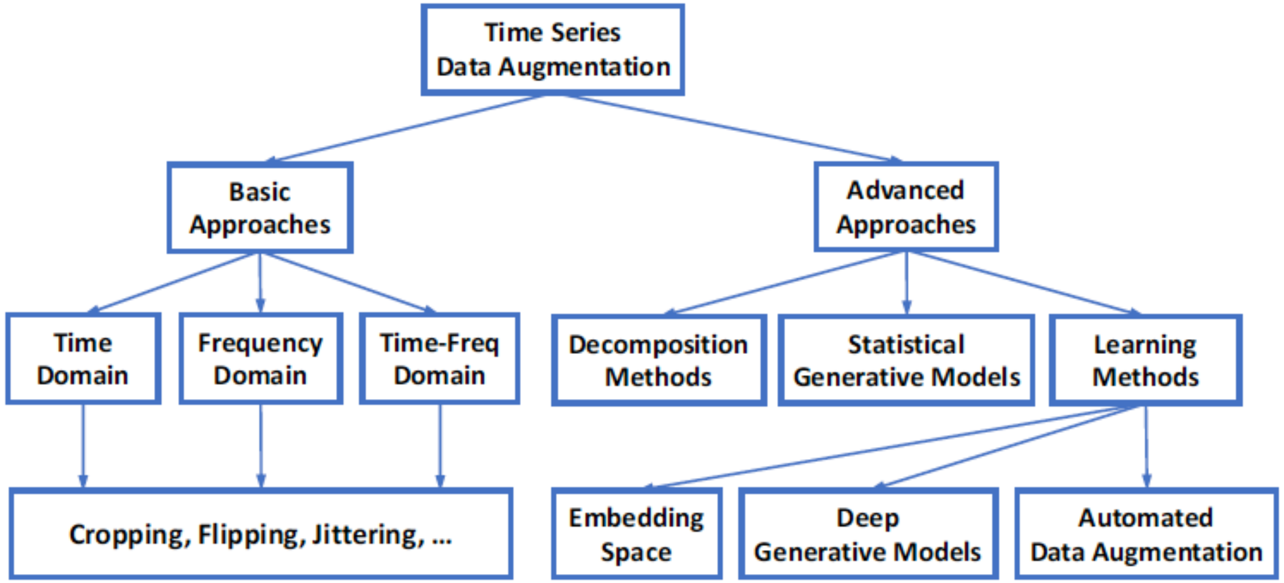
Challenges of time-series data augmentation

- “The intrinsic properties of time series data are not fully utilized in current data augmentation methods.”
- “One unique property of time series data is the so-called temporal dependency.”
- “This becomes more complicated when we model multivariate time series where we need to consider the potentially complex dynamics of these variables across time.”



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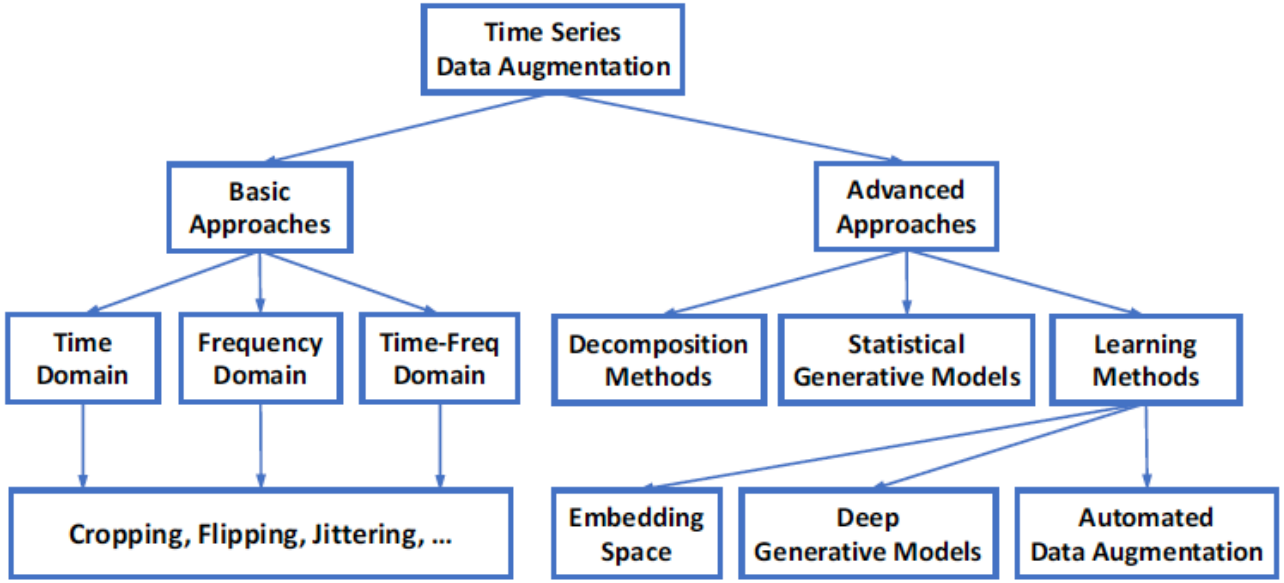
What is discussed in this paper?

Data augmentation methods for not only

- time-series classification, but also for
- time-series forecasting, and
- anomaly detection.

Also, a taxonomy of different types of augmentations (as shown in the figure).



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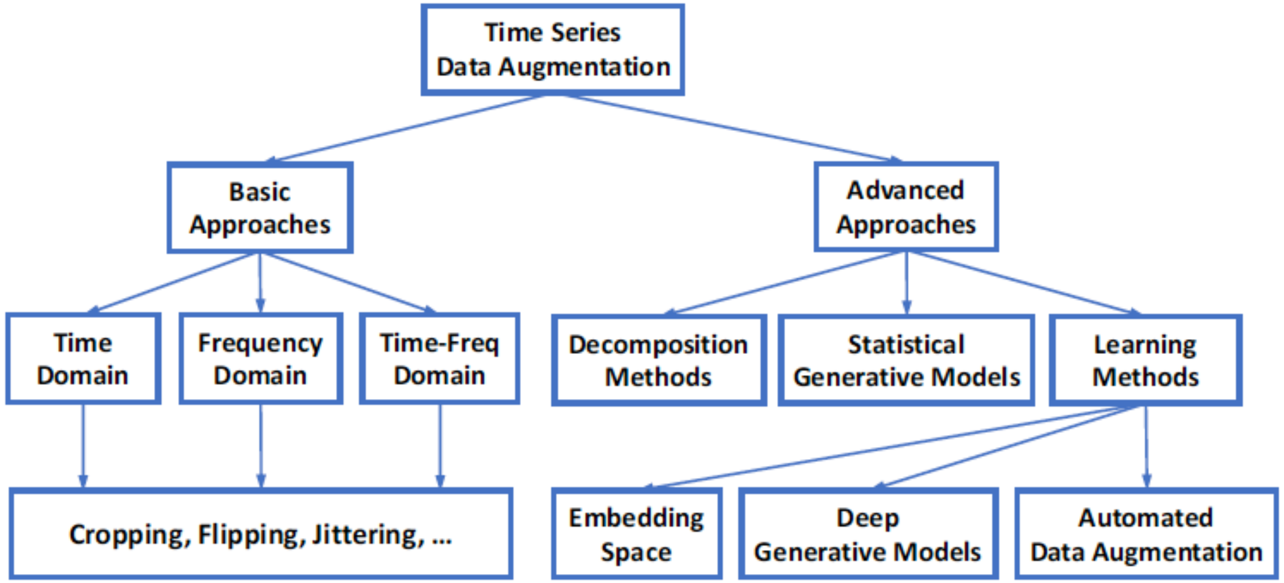
Time domain – window cropping

- “It is a subsample method to randomly extract continuous slices from the original time series.
- The length of the slice is a tunable parameter.
- For classification problem, the labels of sliced samples are the same as the original time series.
- For anomaly detection problem, the anomaly label will be sliced along with value series.”



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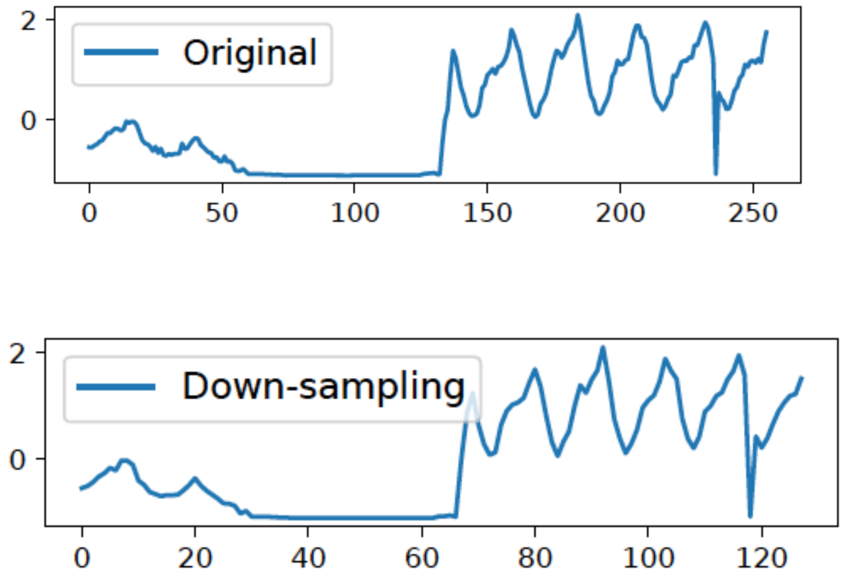
Time domain – window warping

- “This method selects a random time range, then compresses (down sample) or extends (up sample) it, while keeps other time range unchanged.”

- “Window warping would change the total length of the original time series, so it should be conducted along with window cropping for deep learning models.”



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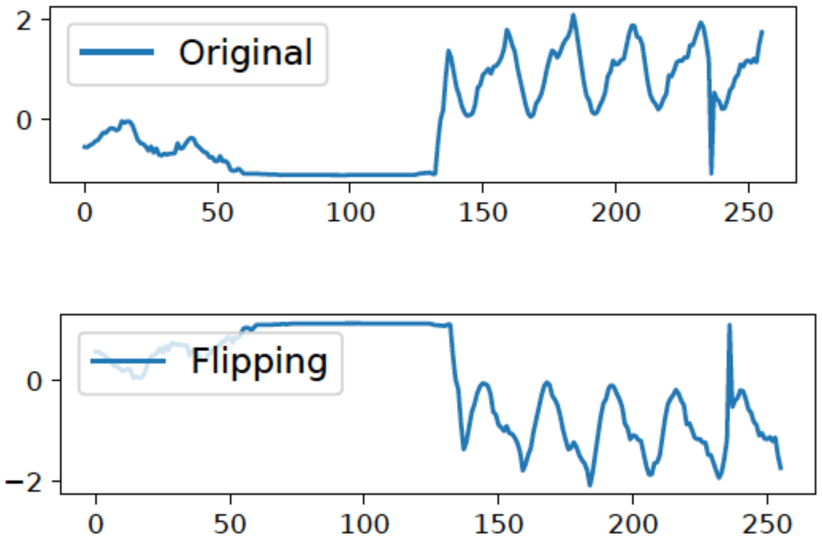
Time domain – flipping

- Flipping generates the new sequence $x'_1, \cdots, x'_N$ by flipping the sign of original time series $x_1, \cdots, x_N,$. Here, $x'_t = -x_t$.

- “The labels are still the same, for both anomaly detection and classification, assuming we have symmetry between up and down directions.”



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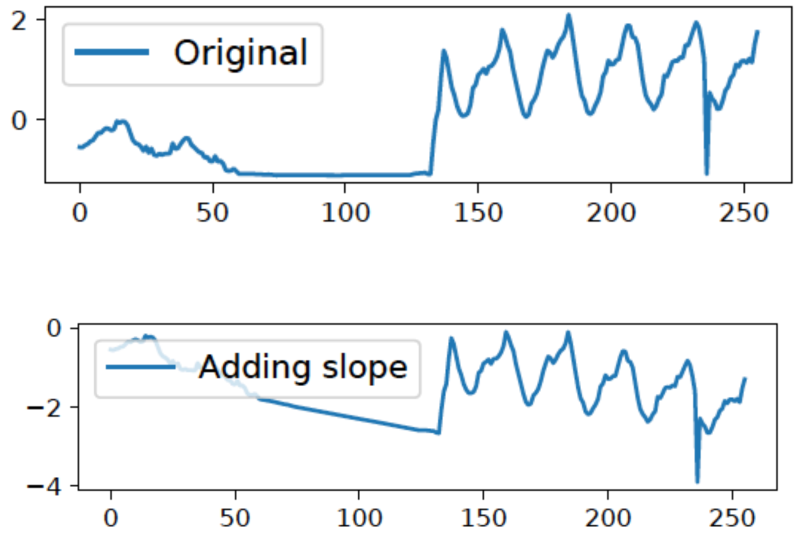
Time domain – noise injection

- Noise injection is a method by injecting small amount of noise/outlier into time series without changing the corresponding labels.

- This includes injecting Gaussian noise, spike, step-like trend, and slope-like trend, etc.



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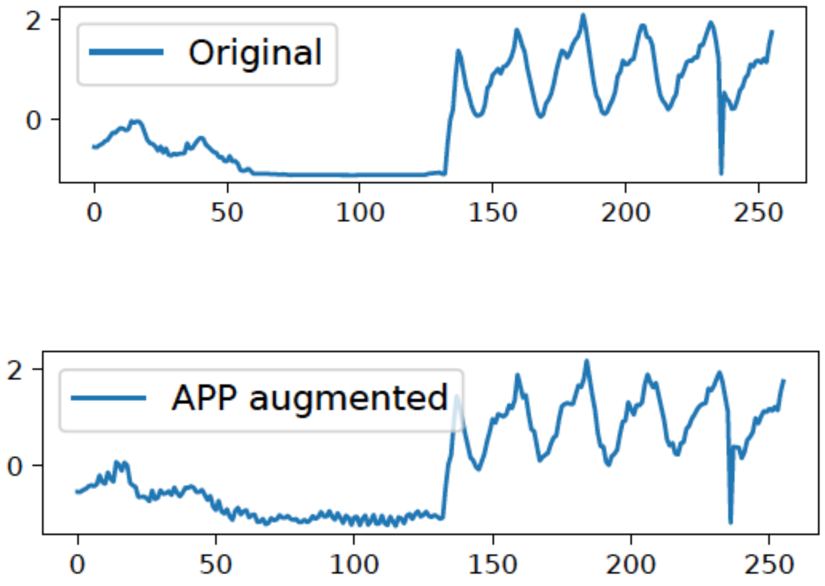
Frequency domain – Amplitude and Phase Perturbation (APP)

anomaly detection by convolutional neural network. Specifically, for the input time series $x_1, \cdots, x_N$, its frequency spectrum $F(\omega_k)$ through Fourier transform is calculated as:

$$F(\omega_k) = \frac{1}{N}\sum_{t=0}^{N-1} x_t e^{-j\omega_k t} = A(\omega_k)\exp[j\theta(\omega_k)] \quad (1)$$

where $\omega_k = \frac{2\pi k}{N}$ is the angular frequency, $A(\omega_k)$ is the amplitude spectrum, and $\theta(\omega_k)$ is the phase spectrum. For perturbations in amplitude spectrum $A(\omega_k)$, the amplitude values of randomly selected segments are replaced with Gaussian noise by considering the original mean and variance in the amplitude spectrum. While for perturbations in phase spectrum $\theta(\omega_k)$, the phase values of randomly selected segments are added by an extra zero-mean Gaussian noise in the phase spectrum. The amplitude and phase perturbations



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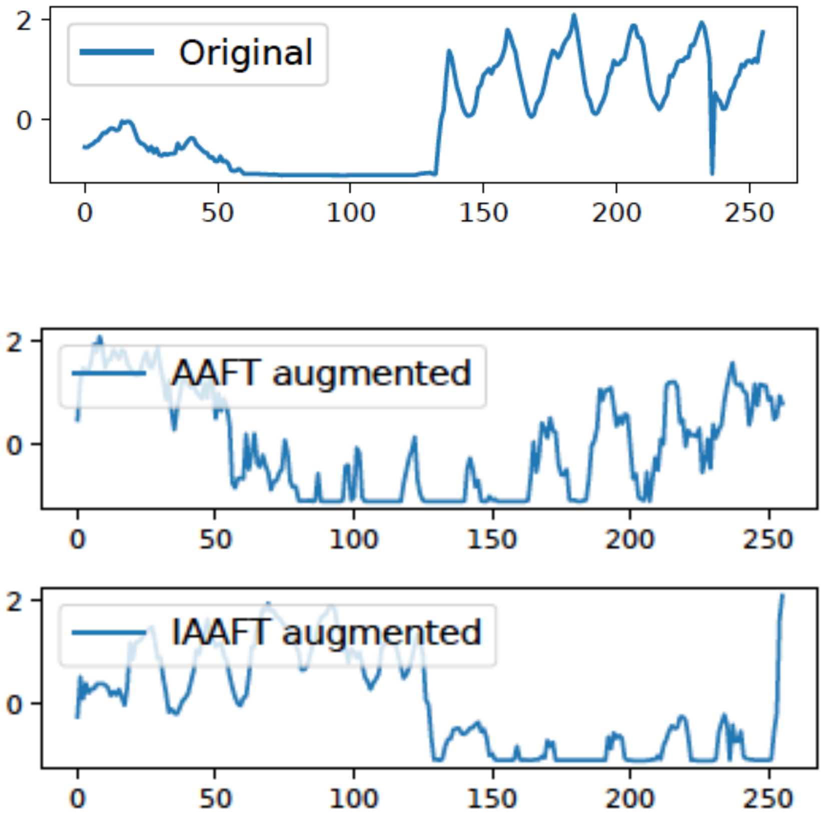
Frequency domain – AFFT and IAFFT

- Surrogate data to improve the classification performance of rehabilitative time series in deep neural network.
- (AAFT) and the iterated AAFT (IAAFT)
- The main idea is to perform random phase shuffle in phase spectrum after Fourier transform and then perform rank-ordering of time series after inverse Fourier transform.
- The generated time series from AAFT and IAAFT can approximately preserve the temporal correlation, power spectra, and the amplitude distribution of the original time series.



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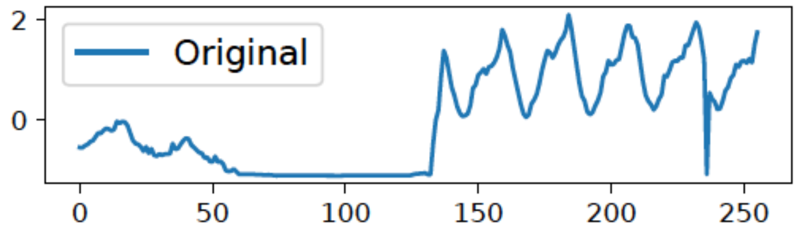
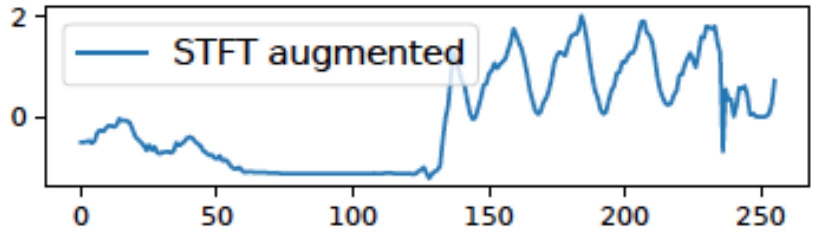
Time-Frequency domain – STFT

- Short Fourier transform (STFT) to generate time-frequency features for sensor time series, and conduct data augmentation on the time-frequency features
- Two augmentation techniques are proposed. One is the local averaging based on a defined criteria with the generated features appended at the tail end of the feature set. Another is the shuffling of feature vectors to create variation in the data.





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Time-series classification with and without Augmentation

Dataset: Alibaba cloud monitoring system
Different noises are injected and tested for robustness
Augmentation methods: cropping, warping, and flipping

Outlier injection	w/o aug	w/ aug	Improvement
spike	96.26%	96.37%	0.11%
step	93.70%	95.62%	1.92%
slope	95.84%	96.16%	0.32%

Table 1: Accuracy improvement from data augmentation under outlier injection in time series classification.

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Time-series forecsating with and without Augmentation

- Datasets: Electricity, Traffic, m4-hourly, m4-daily, m4-weekly

Dataset	DeepAR			Transformer		
	w/o aug	w/ aug	ARI	w/o aug	w/ aug	ARI
electricity	0.87	0.97	1.92%	1.04	1.11	−2%
traffic	0.66	0.80	−12%	0.70	0.91	−16%
m4-hourly	6.33	5.35	56%	7.77	7.87	38%
m4-daily	4.88	4.48	10%	7.85	7.38	37%
m4-weekly	12.00	9.34	76%	6.62	7.09	23%

Table 3: Time seires forecasting improvement from data augmentation based on MASE.

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Time-series anomaly detection with and without Augmentation

- Dataset: Yahoo!
- Algorithms: Raw, Decomposed, Decomposed with augmentation

Augmentations: flipping, cropping, label expansion, and APP based augmentation in frequency domain

Algorithm	Precision	Recall	F1
U-Net-Raw	0.473	0.351	0.403
U-Net-DeW	0.793	0.569	0.662
U-Net-DeWA (w/ aug)	0.859	0.581	0.693

Table 2: Time series anomaly detection improvement from data augmentation based on precision, recall, and F1 score.

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