High-Performance Time Series Augmentation Library

Interim Presentation

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Introduction

1. Time Series...What?
   - Finite Sequence
   - Time ordered indexing
   - Discrete Timestamps
   - Overlapping/Non-Overlapping

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2. Why Augment?
   - Improve Model Generalization
   - Granular Data Analysis
   - Simulate Real-World Noise
   - Overlapping/Non-Overlapping

Insights From The Paper (Wen et al. 2020)

1. Time Domain Transformations
   - Computationally Cheap
   - Good baseline

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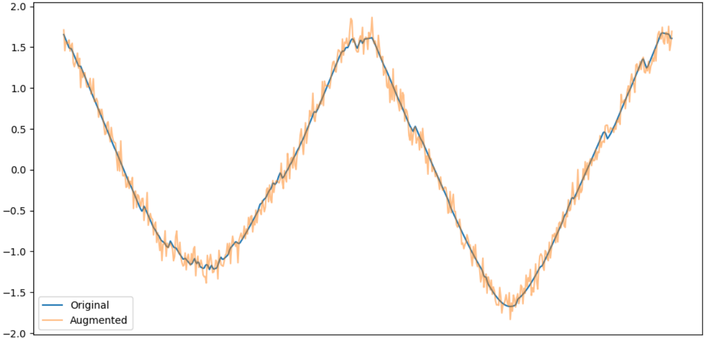
3. Impact
   - 2% Classification Accuracy Improvement
   - 20-30% Improvement - Anomaly Detection F1 Score
   - Reduced MASE error - Forecasting Use Cases

Project Plan

1. Implementation of core time series augmentation methods in Rust
   - Basic transformations

Basic Transformations (Um et al. 2017)

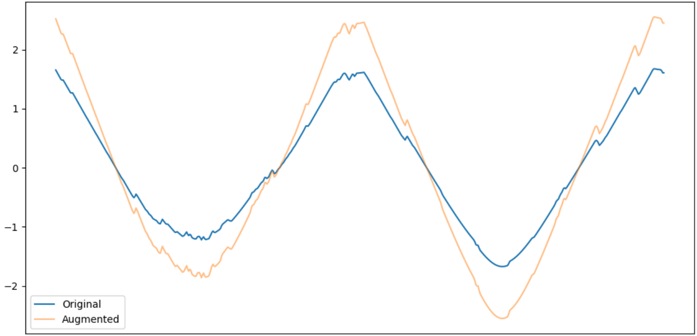
Jittering: Add white noise to the data



Parameters: σ of Gaussian noise

Basic Transformations (Um et al. 2017)

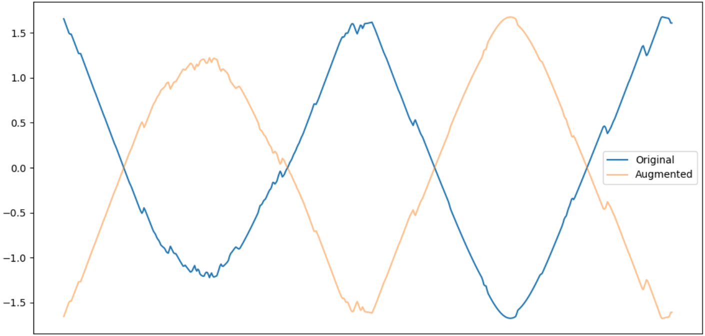
Scaling: Scale data points by random factor



Parameters: Min and max of random factor

Basic Transformations (Um et al. 2017)

Rotation: "Rotate" data 180° around an anchor



Parameters: Anchor value

Basic Transformations (Um et al. 2017)

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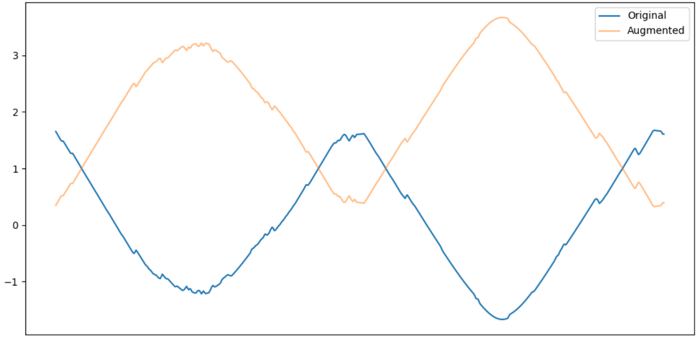
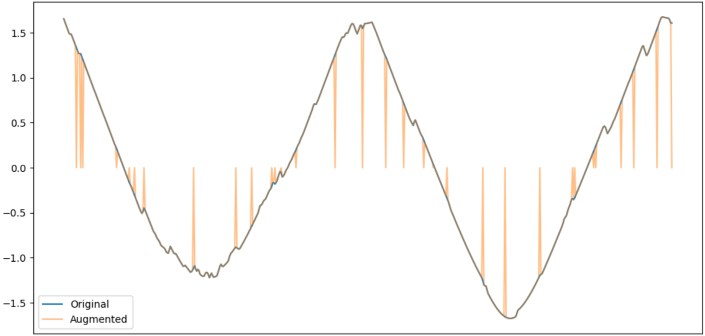


Parameters: Anchor value

Basic Transformations (tsaug)

Drop: Drop percentage of data points



Parameters: Percentage and default value

Basic Transformations (tsaug)

Special Transformations:

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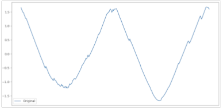
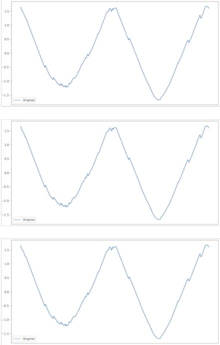
Special Transformations:

Repeat: Repeat each series in the dataset *n* times



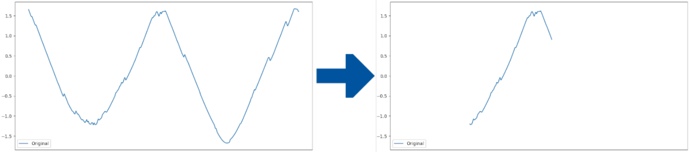


Basic Transformations (tsaug)

Special Transformations:

Repeat: Repeat each series in the dataset *n* times

Crop: Crop each time series into a random continuous slice of specified size



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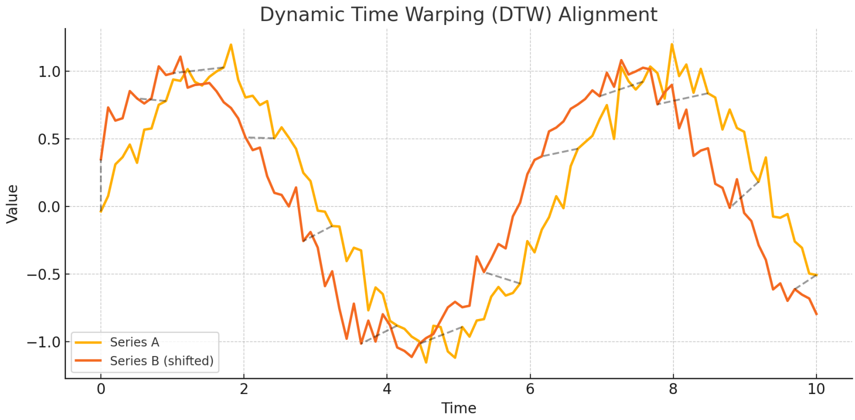
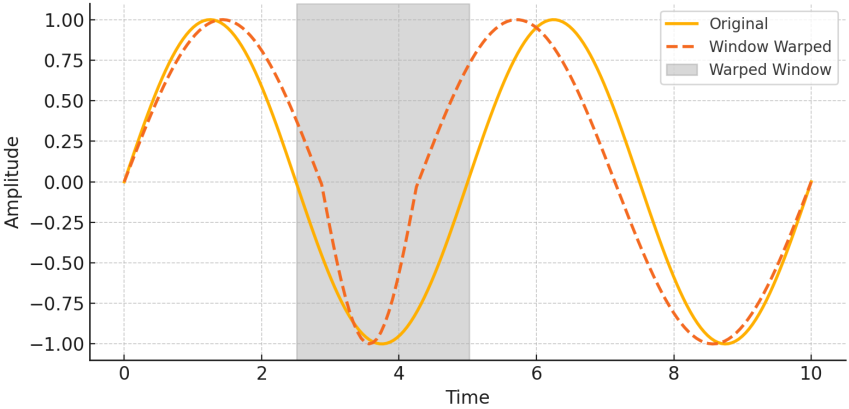
Time Warping

Dynamic Time Warping (DTW): Finds optimal warping path to generate different temporal variations.



Time Warping

Window Warping: Select a random window in the time series and stretch or compress it



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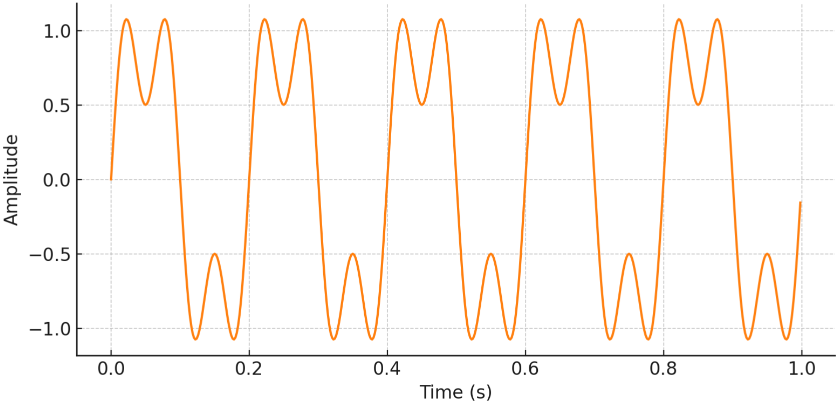
Frequency-Domain Transformations

Fast Fourier Transform (FFT): Converts a time-domain signal into its frequency components

- Time Domain



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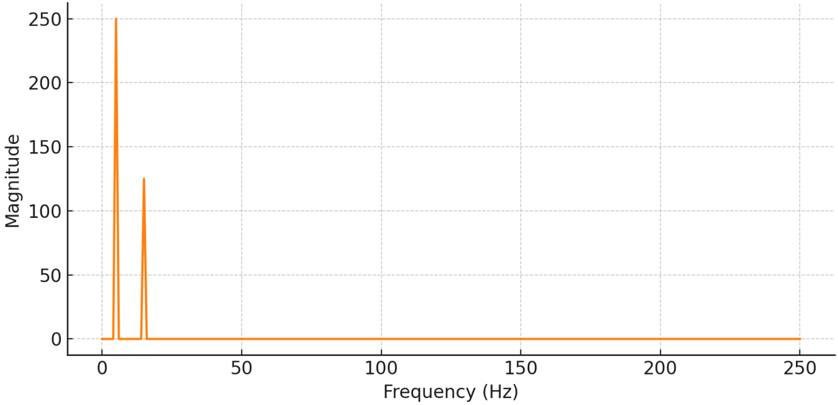
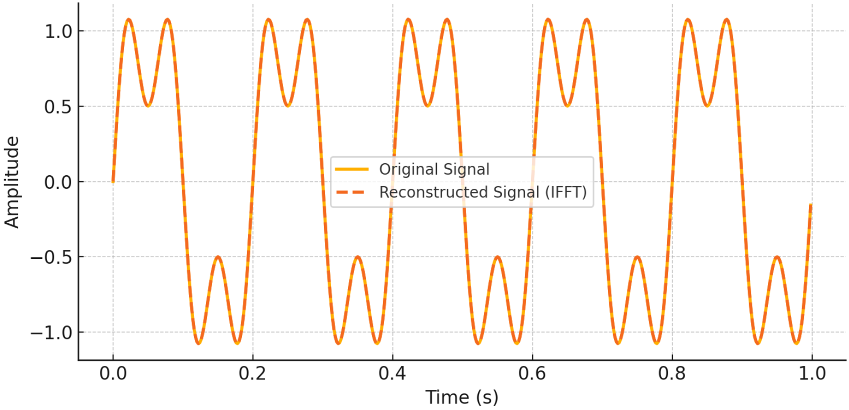


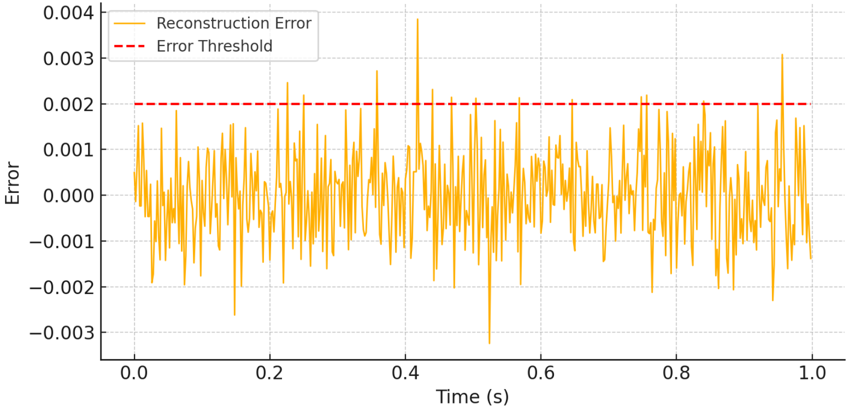
Frequency-Domain Transformations

Inverse Fast Fourier Transform (IFFT): Converts frequency-domain data back to the time domain.



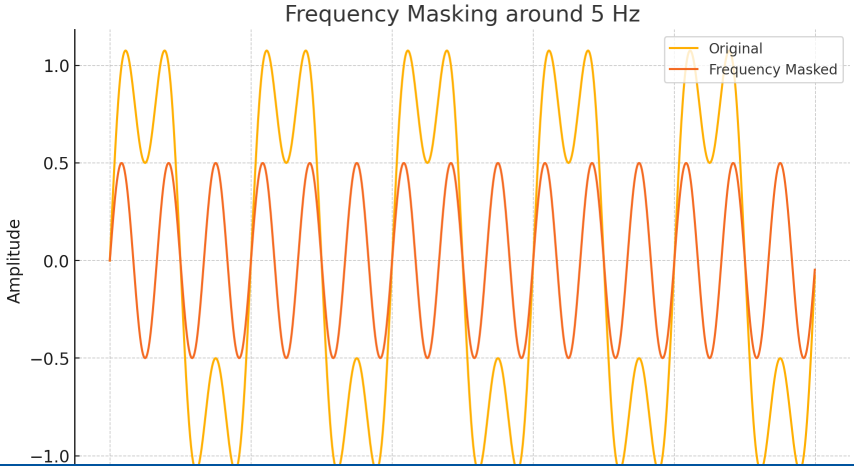
Frequency-Domain Transformations

Inverse Fast Fourier Transform (IFFT): Reconstruction error is negligible (below numerical threshold), ensuring lossless transform.



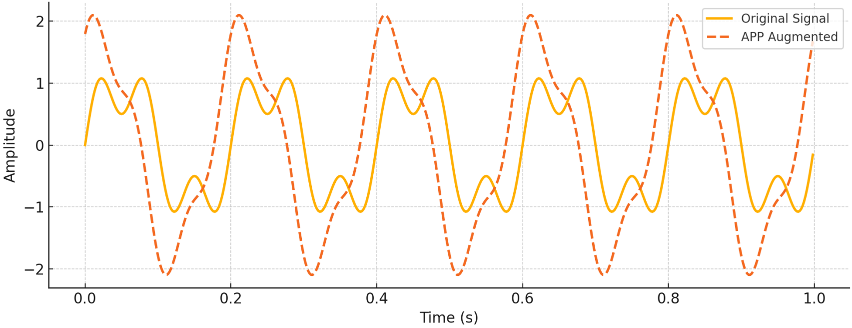
Frequency-Domain Transformations

Frequency Masking: Randomly zero out contiguous FFT bins around a center frequency to simulate narrowband interference or dropout in sensors.



Frequency-Domain Transformations

Amplitude & Phase Perturbation (APP): Add small Gaussian noise to each bin's magnitude and phase to introduce realistic spectral jitter while preserving overall structure



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    - Noise injection methods

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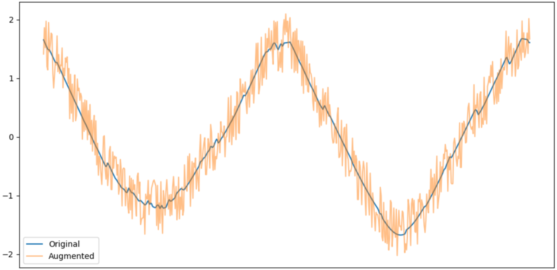

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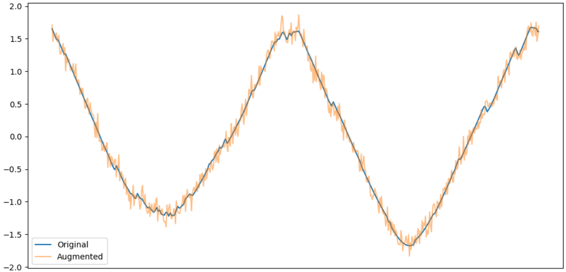
AddNoise augmenter that supports different kinds of noise (according to Wen et al. 2020):

- Uniform
- Gaussian (like jittering)



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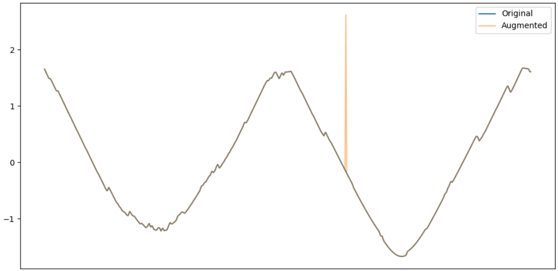
- Gaussian (like jittering)
- Spike



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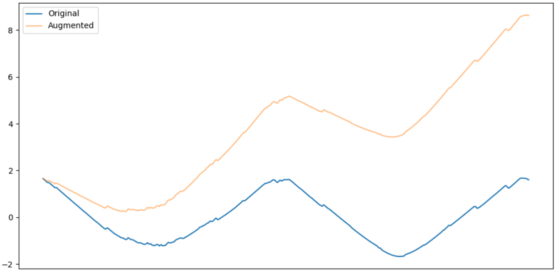
AddNoise augmenter that supports different kinds of noise (according to Wen et al. 2020):

- Uniform
- Gaussian (like jittering)
- Spike
- Slope



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   - Single-method augmentation calls

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   - Composable augmentation pipelines

Implementation - Rust

Every augmenter implements the Augmenter trait:

```
pub trait Augmenter {
    fn augment_dataset(&self, input: &mut Dataset) {
        input.features
            .iter_mut()
            .for_each(|x| self.augment_one(x));
    }

    fn augment_one(&self, x: &mut [f64]);
}
```

Implementation - Rust

⇒ Allows us to create "recursive" augmenters:

```rust
pub struct ConditionalAugmenter {
    inner: Box<dyn Augmenter>,
    p: f64,
}

pub struct AugmentationPipeline {
    augmenters: Vec<Box<dyn Augmenter>>,
}
```

Implementation - Rust

Example pipeline:

```rust
let pipeline = AugmentationPipeline::new()
    + Repeat::new(10)
    + Crop::new(100)
    + ConditionalAugmenter::new(
        AddNoise::new(
            NoiseType::Slope,
            Some((0.01, 0.02)),
            None,
            None
        ),
        0.25
    )
    + Jittering::new(0.1);

pipeline.augment_dataset(&mut dataset);
```

Implementation - Python

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- In seperate package to Rust library
- We bind the struct Dataset to pass the data around
- Augmenter structs are exposed to Python as classes
- Limitations with PyO3 don't allow for the same architecture

Implementation - Python

PyO3 makes the binding of the recursive augmenters difficult, so these are fully written in Python for now:

```python
class ConditionalAugmenter:
    def __init__(self, augmenter, probability): ...
    def augment_dataset(self, dataset: Dataset): ...
    def augment_one(self, x): ...

class AugmentationPipeline:
    def __init__(self): ...
    def __add__(self, other): ...
    def augment_dataset(self, dataset: Dataset): ...
    def augment_one(self, x): ...
```

Implementation - Python

Full python example:

```
dataset = pf.Dataset(features, labels)

pipeline = (pf.AugmentationPipeline()
            + pf.Repeat(10)
            + pf.Crop(100)
            + pf.ConditionalAugmenter(
                pf.AddNoise(
                    pf.NoiseType.Slope,
                    bounds=(0.01, 0.02)
                ),
                0.25
            )
            + pf.Jittering(0.1))

pipeline.augment_dataset(dataset)
```

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    - Composable augmentation pipelines
    - Batch processing capabilities
    - Parallel exection options

Project Plan

3. Analyse performance against python library tsaug
   - Execution time benchmarks
   - Memory usage comparisons
   - Quality assessment of augmented data

References

Wen, Qingsong et al. (2020). "Time series data augmentation for deep learning: A survey". In: *arXiv preprint arXiv:2002.12478*.

Um, Terry T et al. (2017). "Data augmentation of wearable sensor data for parkinson's disease monitoring using convolutional neural networks". In: *Proceedings of the 19th ACM international conference on multimodal interaction*, pp. 216–220.