Decomposing time series into trends, seasonality, residuals

Classical timeseries decomposition (ca. 1920's)

Assumptions

- Additive: $Y = T+S+R$
- Multiplicative: $Y = TSR$
- Either way, Y = "f(t) + e(t)"

Basic building blocks

- Trends, T
- Seasonality, S
- Residuals, R

Additive and Multiplicative

We use *statsmodels.tsa.seasonal*

Function:
seasonal_decompose

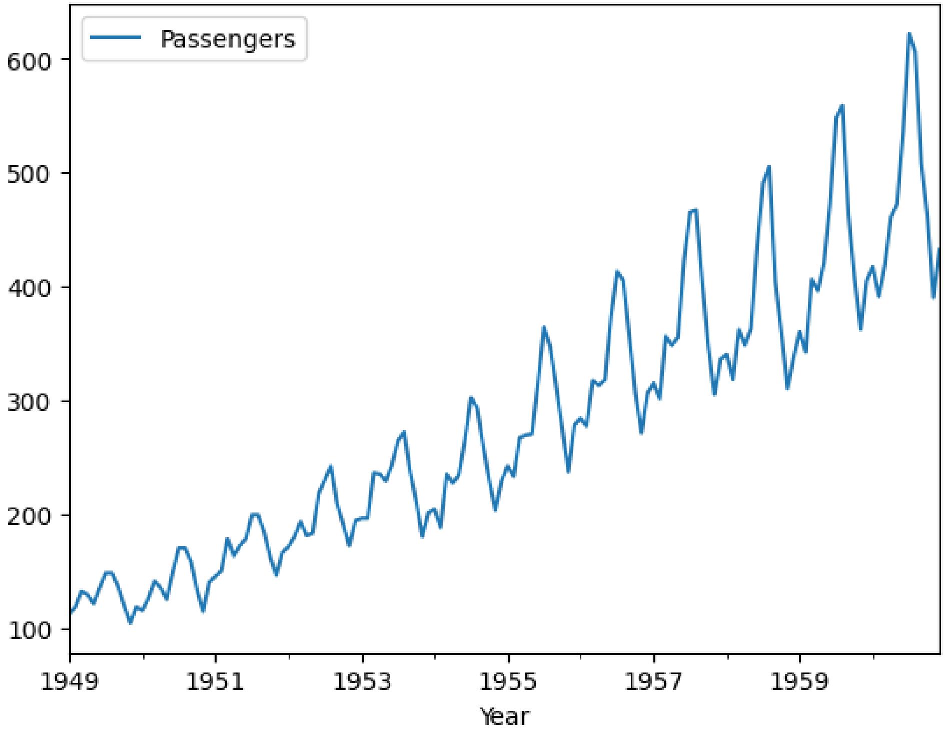
Hyperparameters

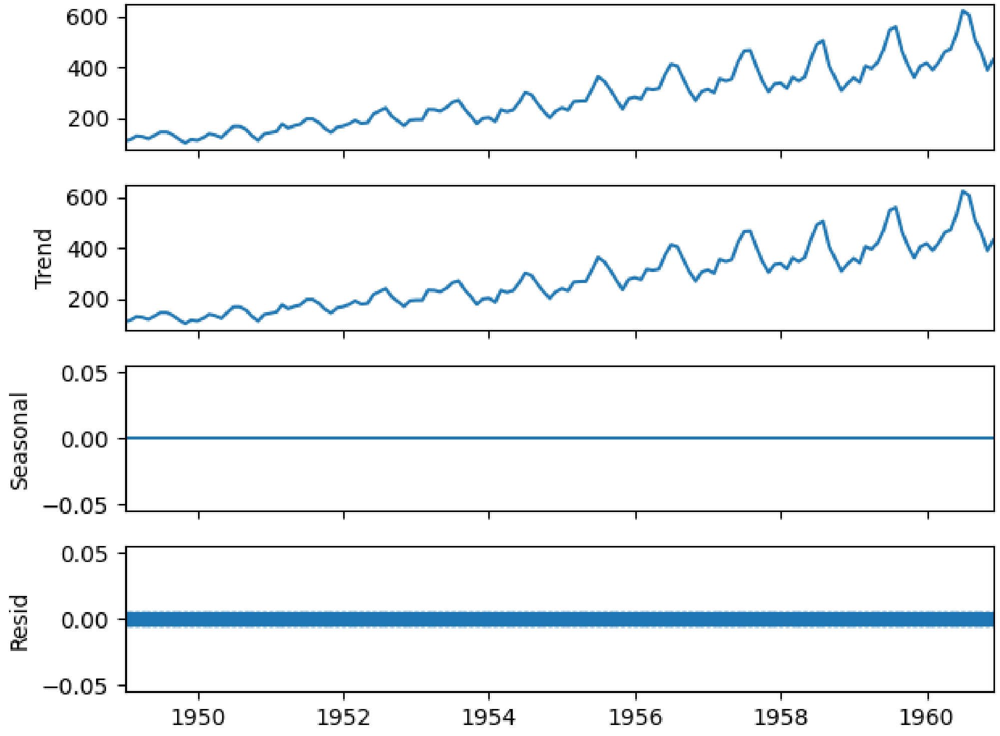
Model (additive/multiplicative/++)

Period (how many datapoints in each season)

Method 1: Additive

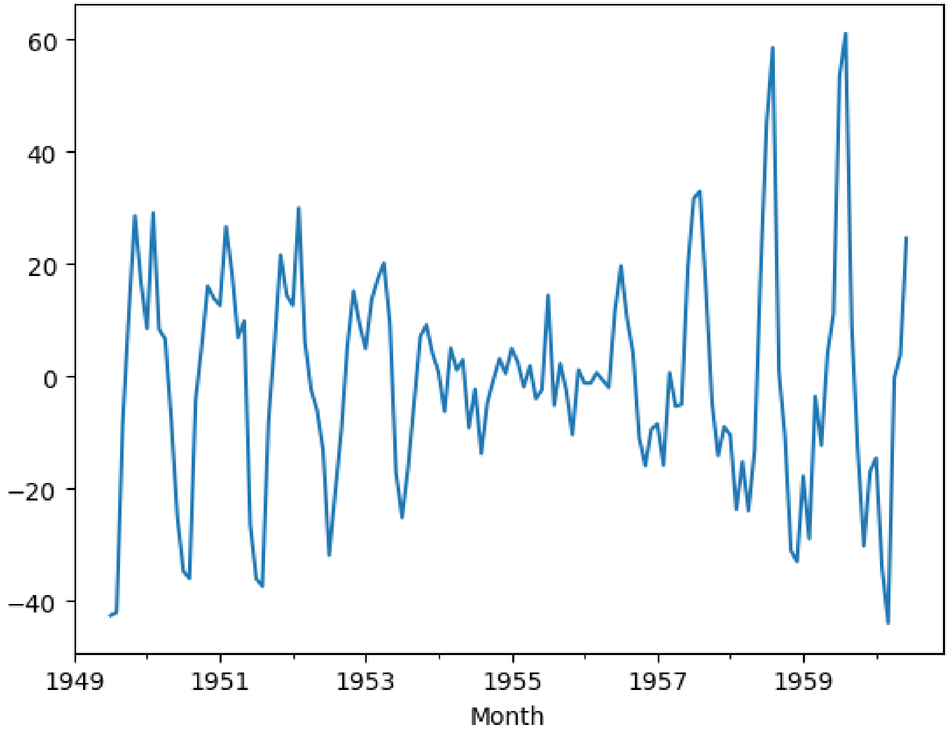
Period = 1

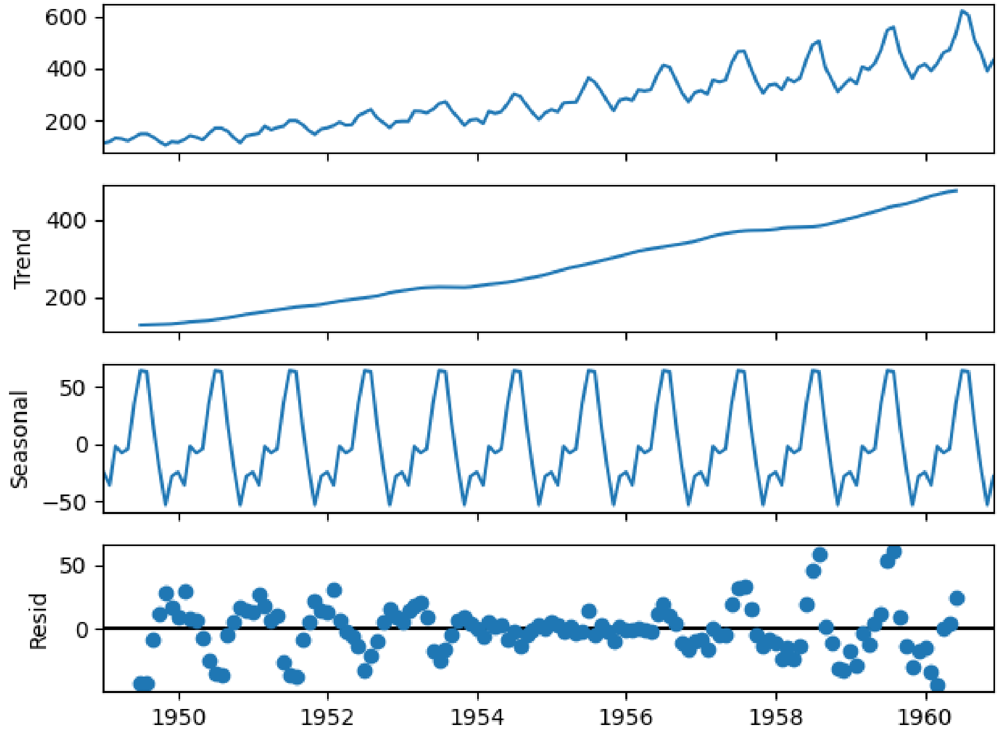




Method 1: Additive

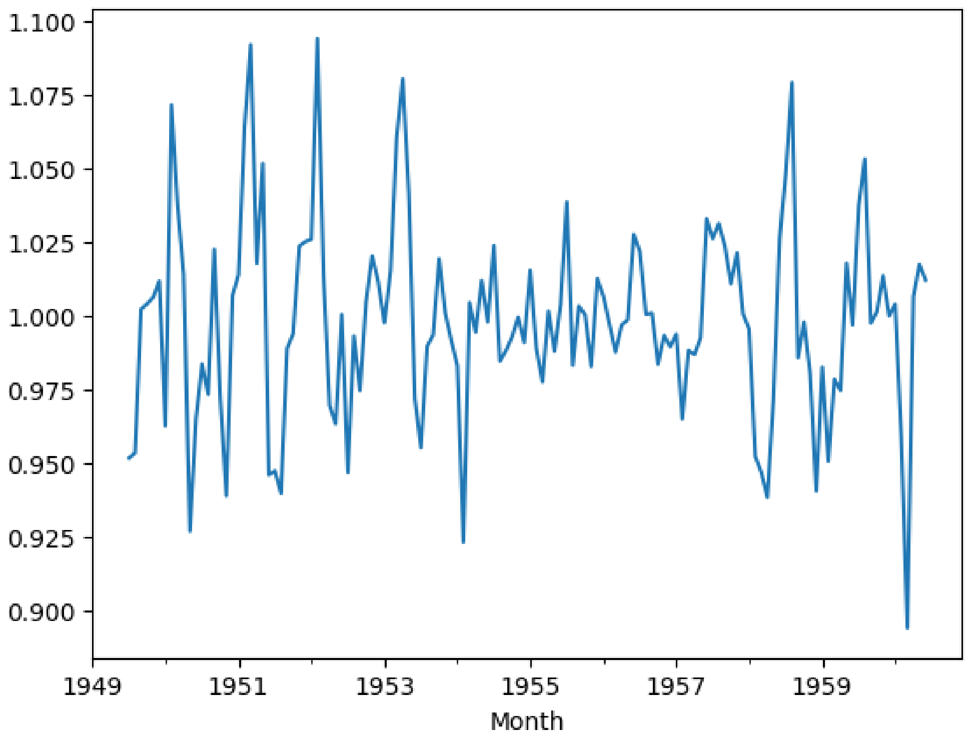
Period = 12

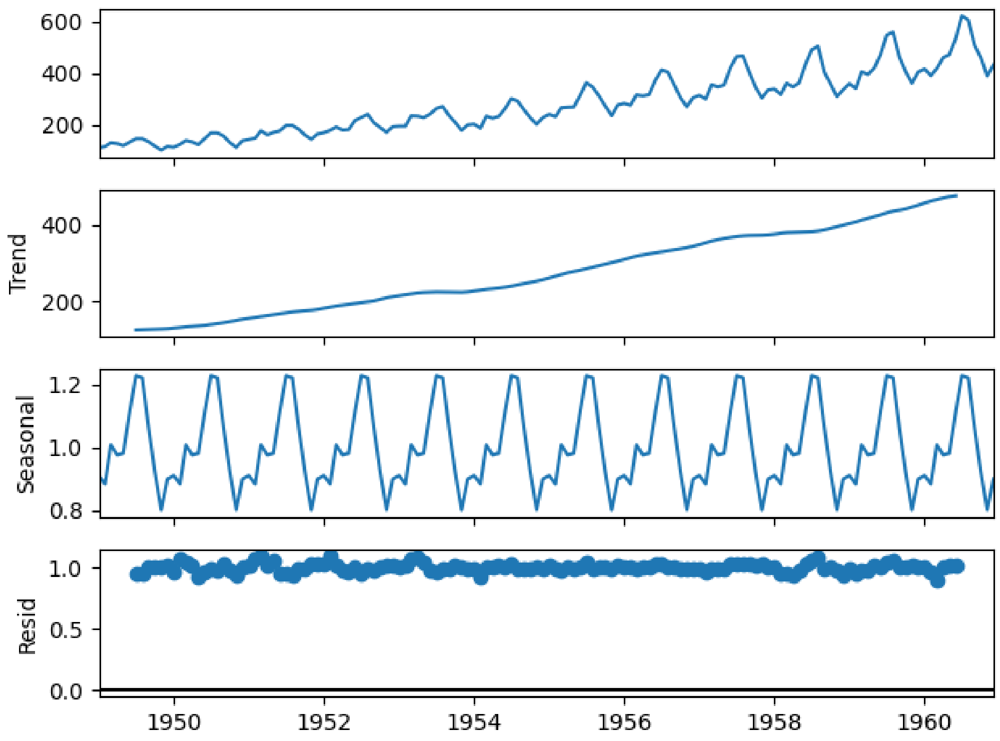




Method 2: Multiplicative

Period = 12





Quick tips

Trends should be "smooth" and aperiodic

Seasons should definitely be periodic

Irregularities should "not have patterns"

And noise "should look random"

If a trend has periods: decompose it further

If a season looks to trend (or have an envelope): decompose it further

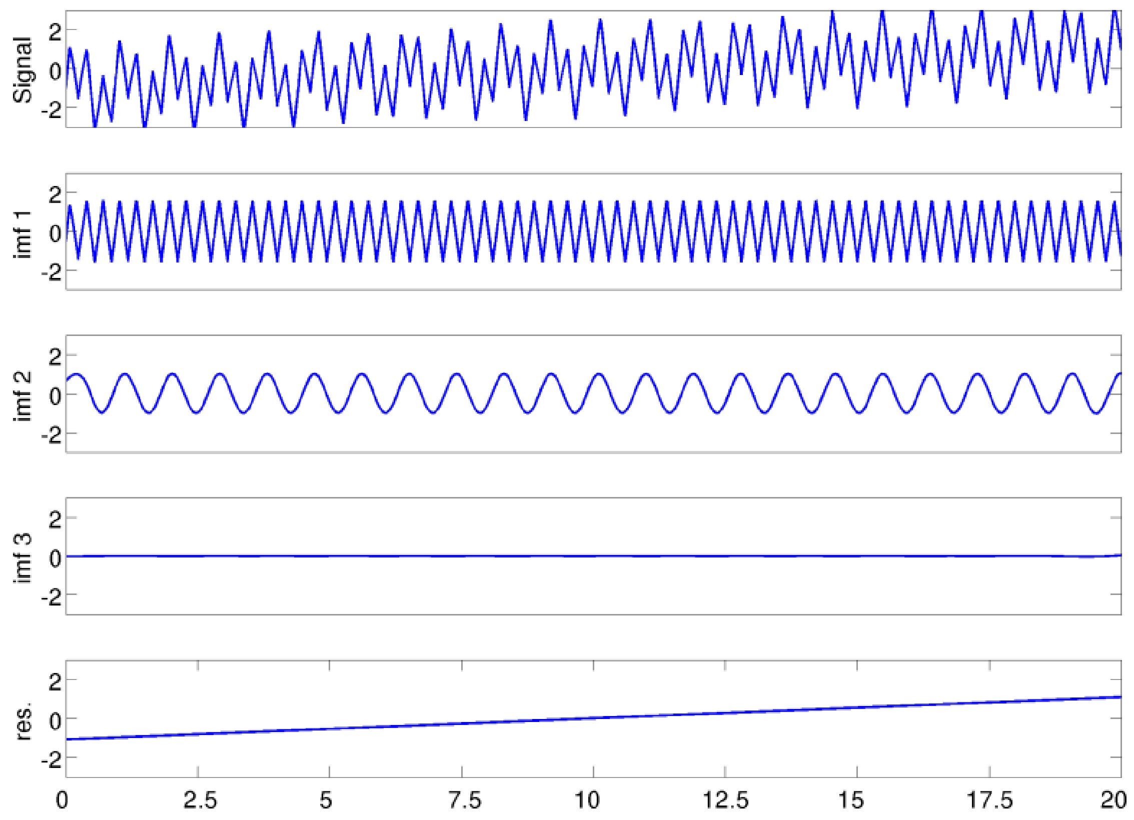
If the noise looks to have patterns: keep changing your model and decomposing further

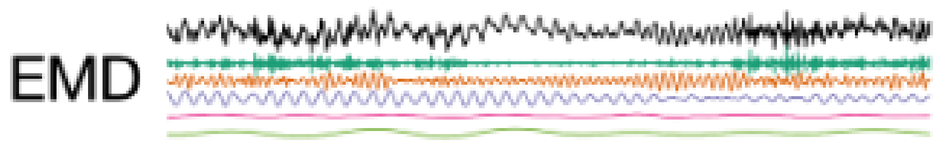
Empirical Mode Decomposition
EMD

EMD Overview

- Decomposes a signal into oscillatory components
- Components known as Intrinsic mode Functions (IMF) + residual components.
- Data-Driven method, operating on nonlinear and nonstationary signals
- Assumes additive timeseries*
- Requires no prior knowledge about the data
- Depends on ***Sifting*** to compute the IMF

Zeiler et al. (2010). Empirical Mode Decomposition - an introduction.





Andrew J. Quinn et al. (2021) EMD: Empirical Mode Decomposition and Hilbert-Huang Spectral Analyses in Python

Sifting Process

(EMD cont')

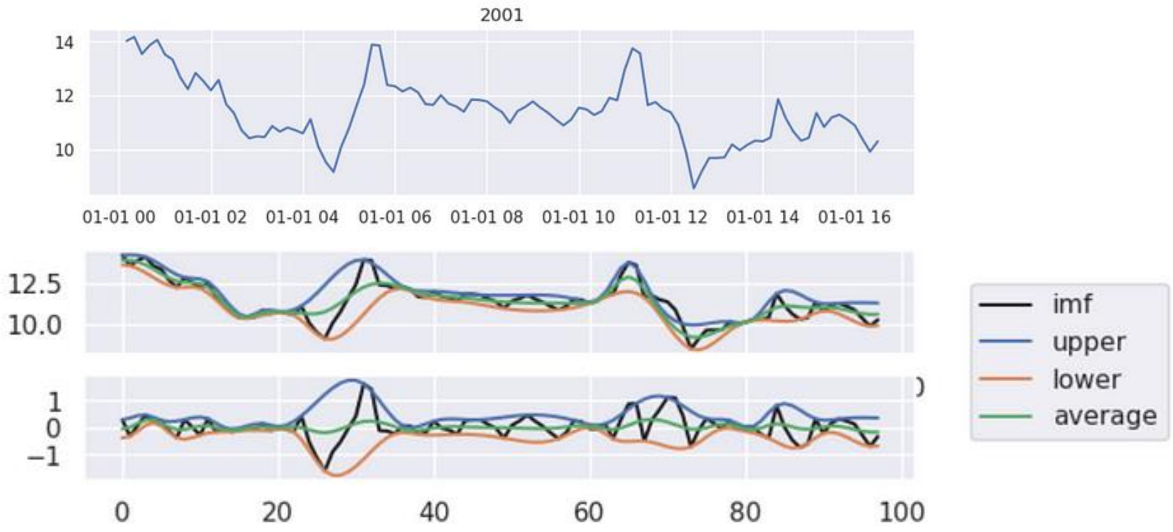


Figure source: AI Mavercik

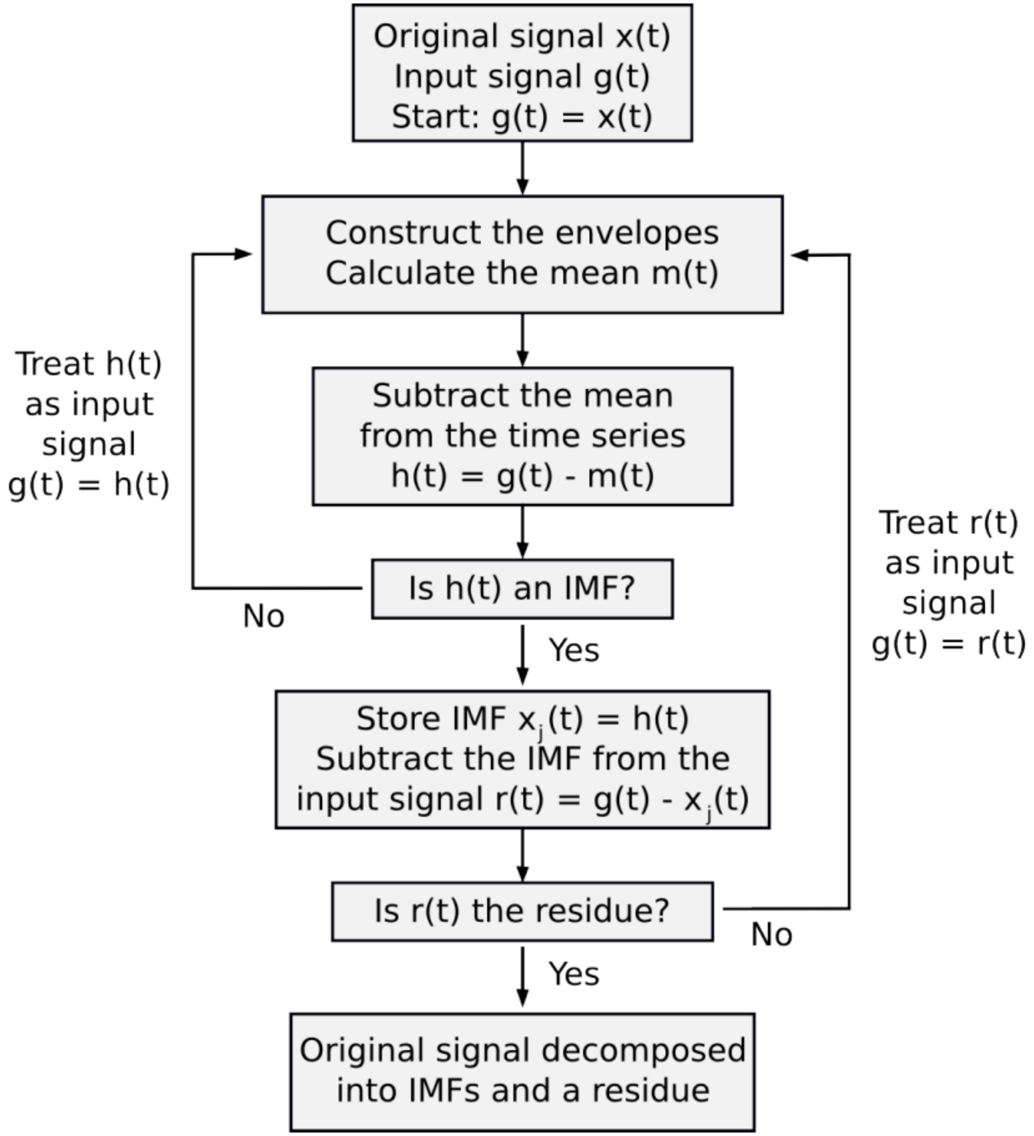


figure: Zeiler et al. (2010). Empirical Mode Decomposition - an introduction.

Limitations

- Mode mixing
- Limited to additive models *

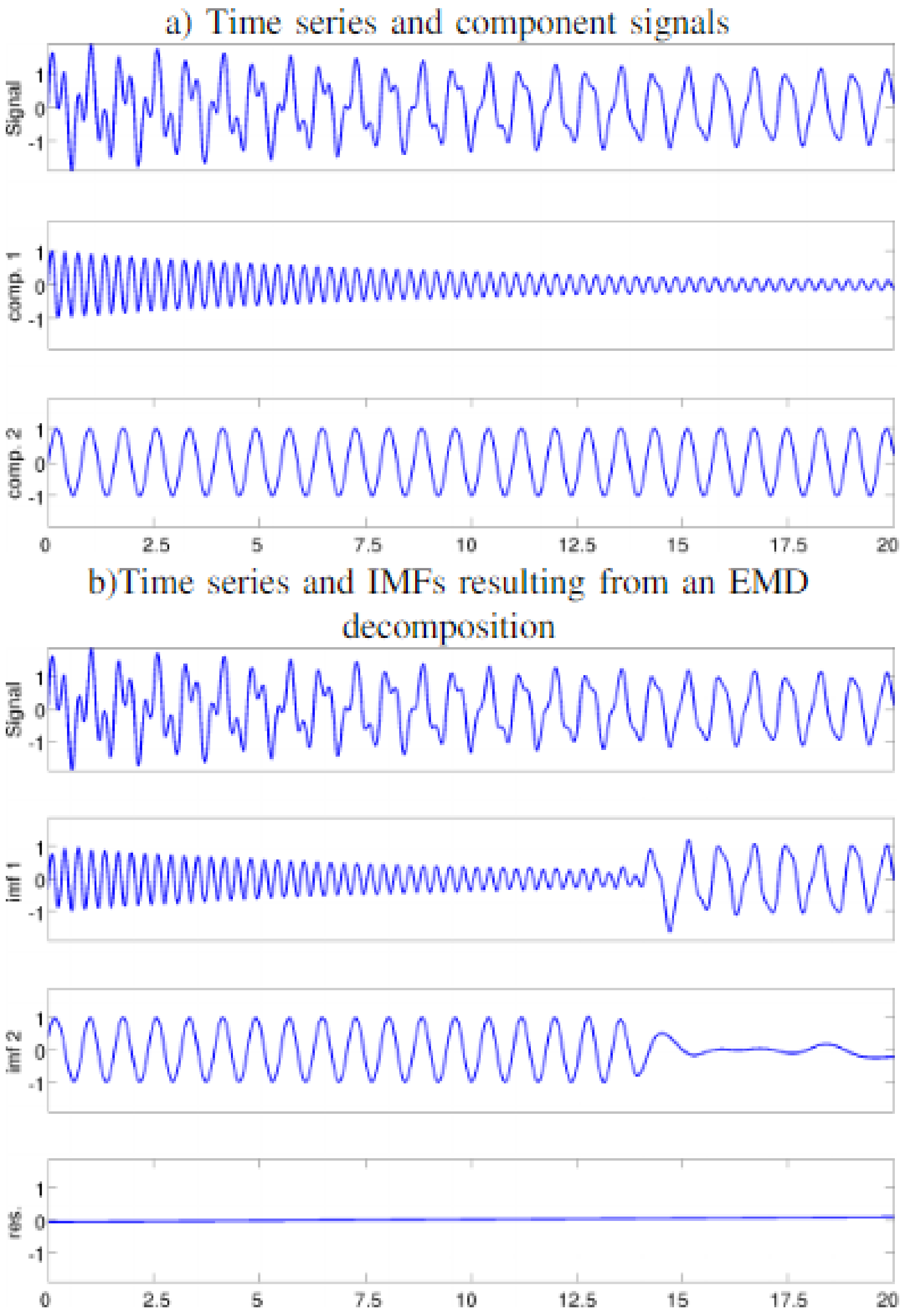
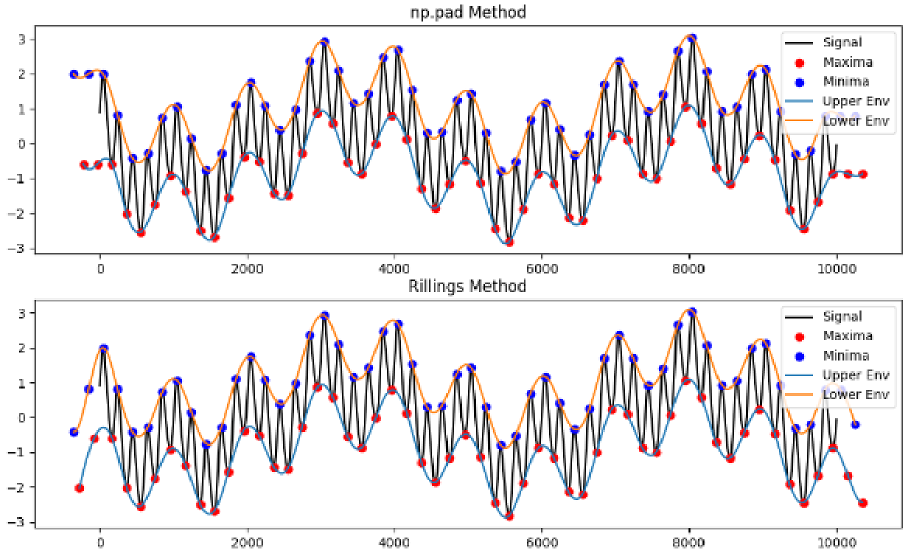


figure: Zeiler et al. (2010). Empirical Mode Decomposition - an introduction.

Limitations

- Sensitive to boundary condition



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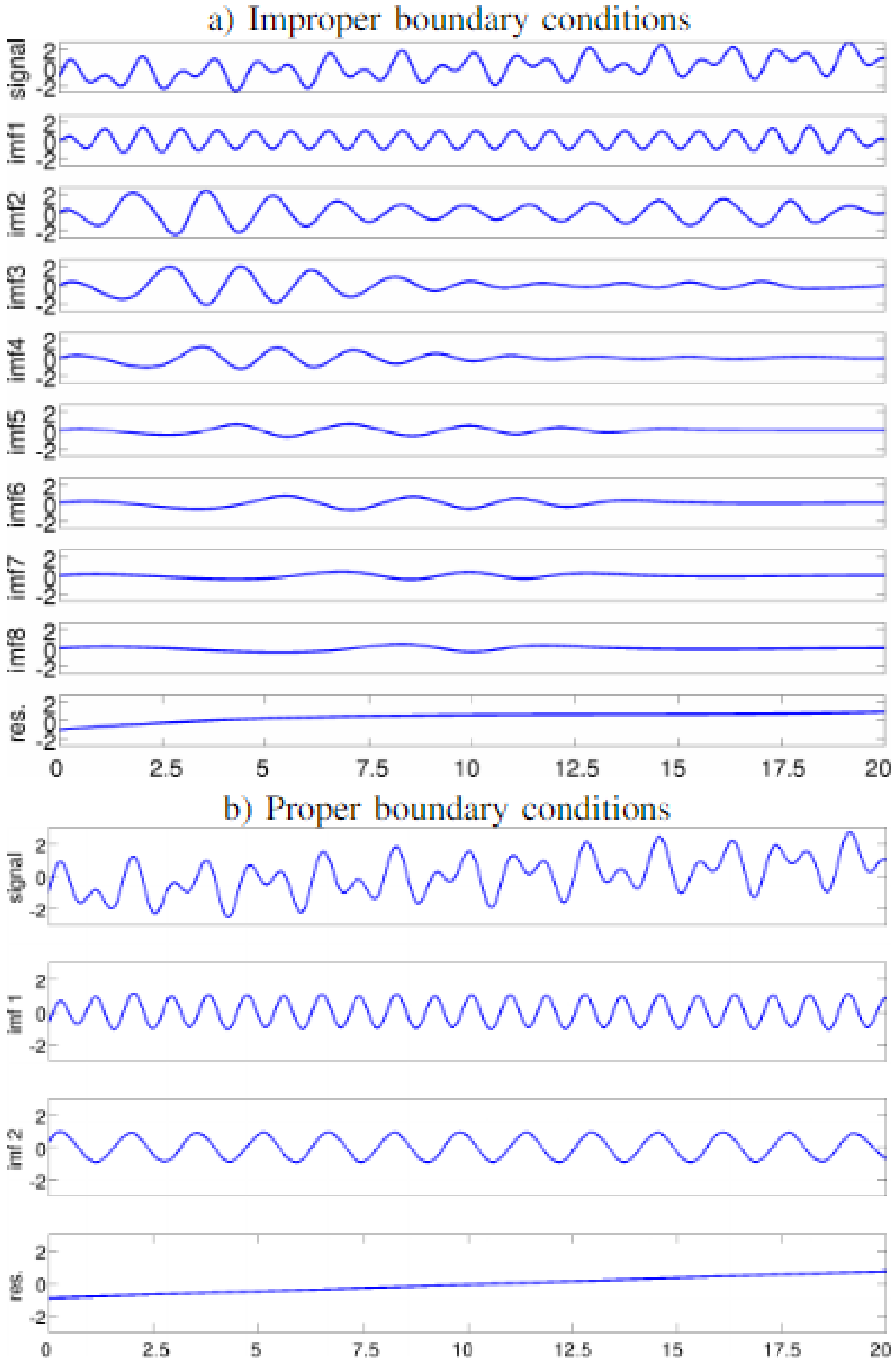
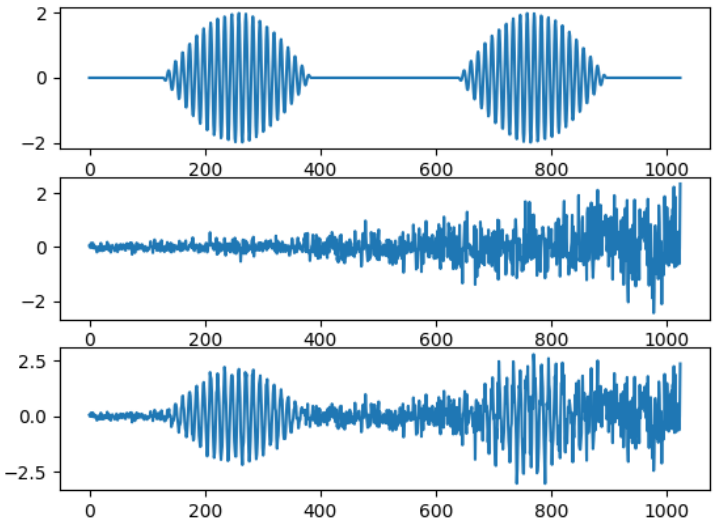
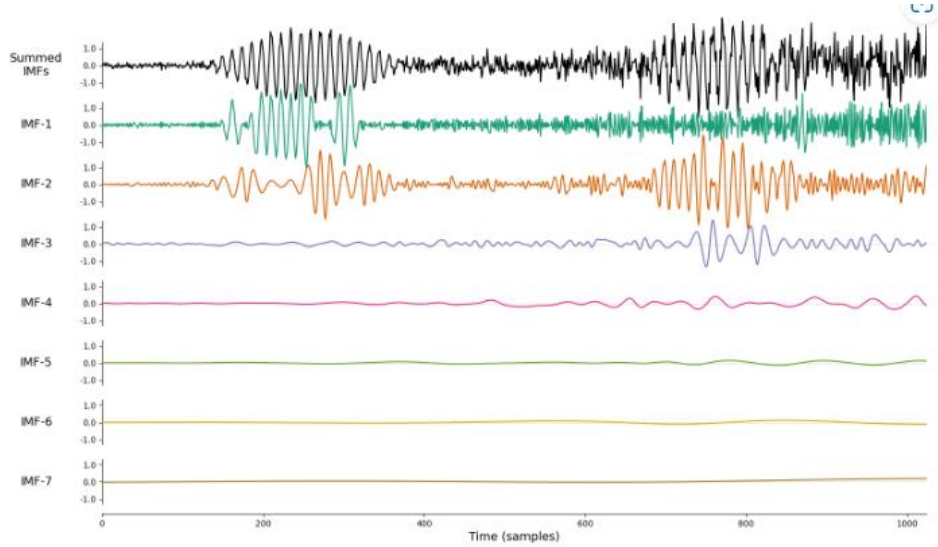


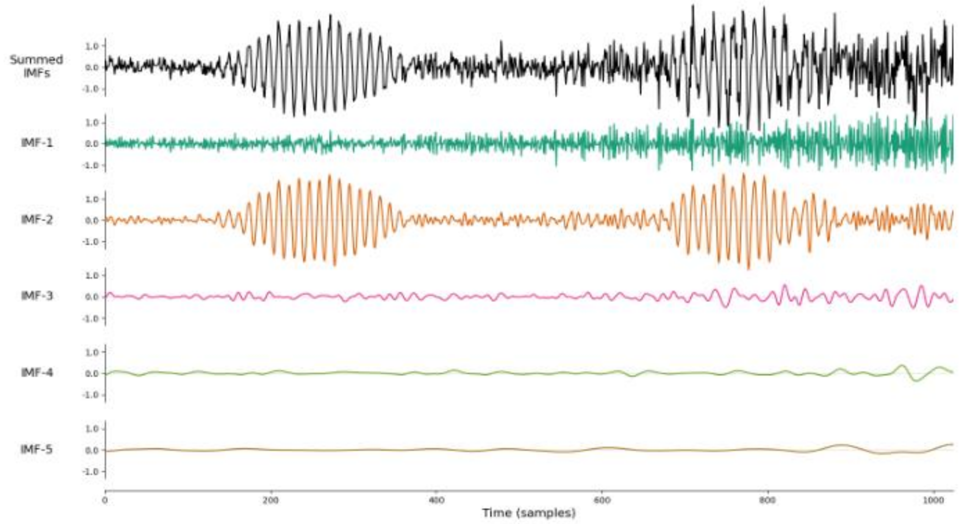
figure: Zeiler et al. (2010). Empirical Mode Decomposition - an introduction.

Other Sifting Variations

- Noise Assisted sifting (ensemble EMD)







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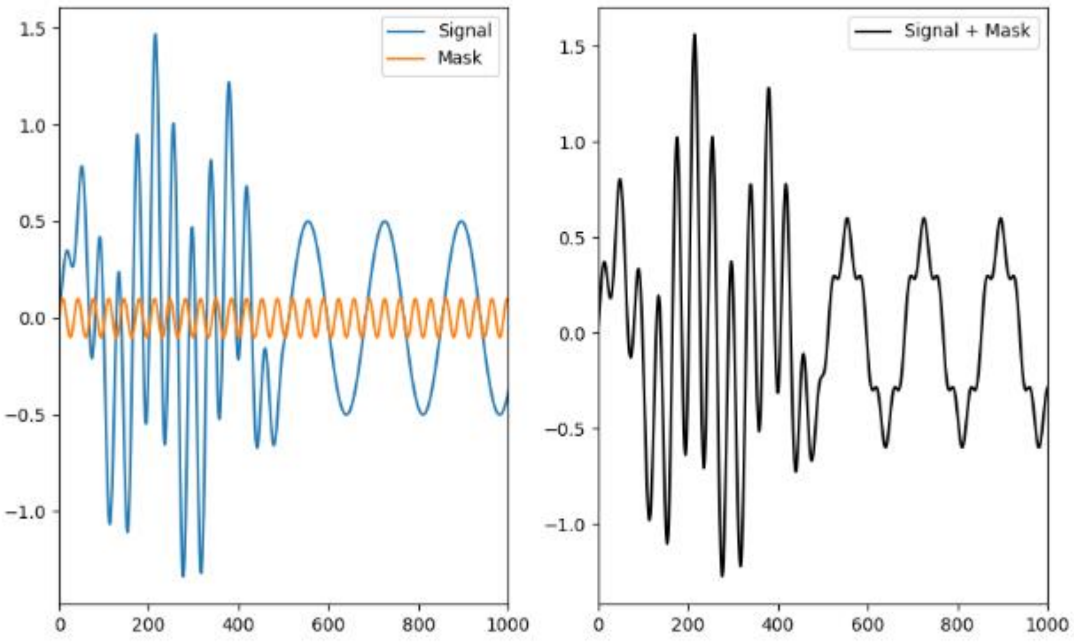
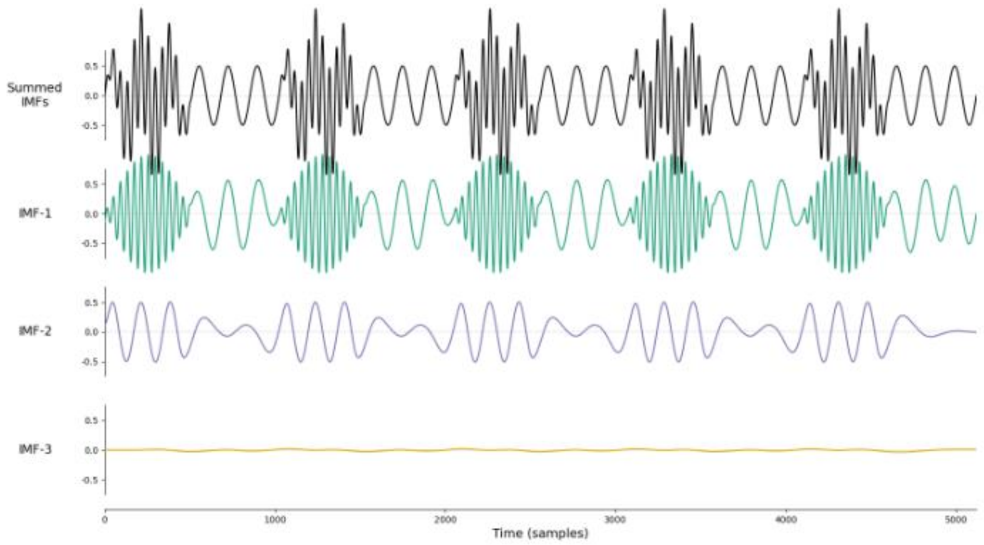
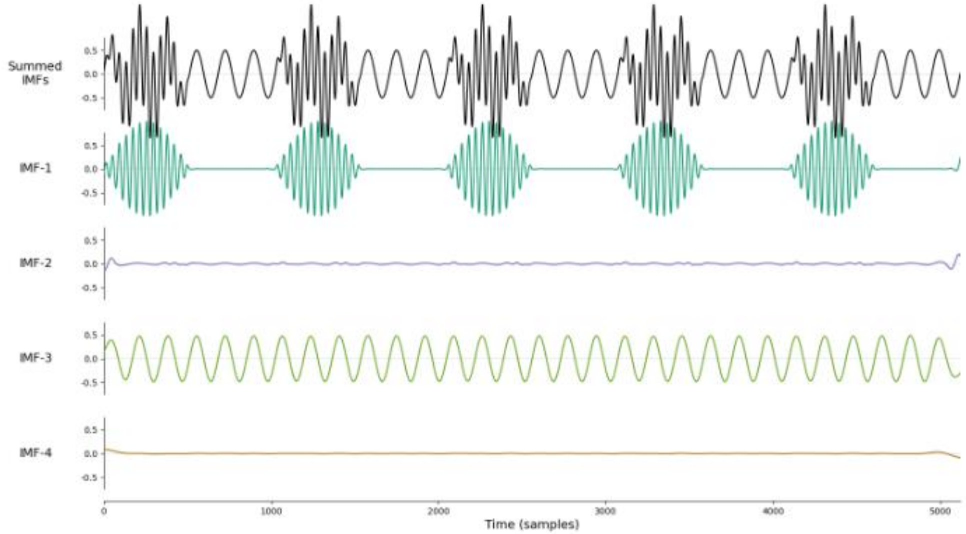
Other Sifting Variations

- Masked Sifting



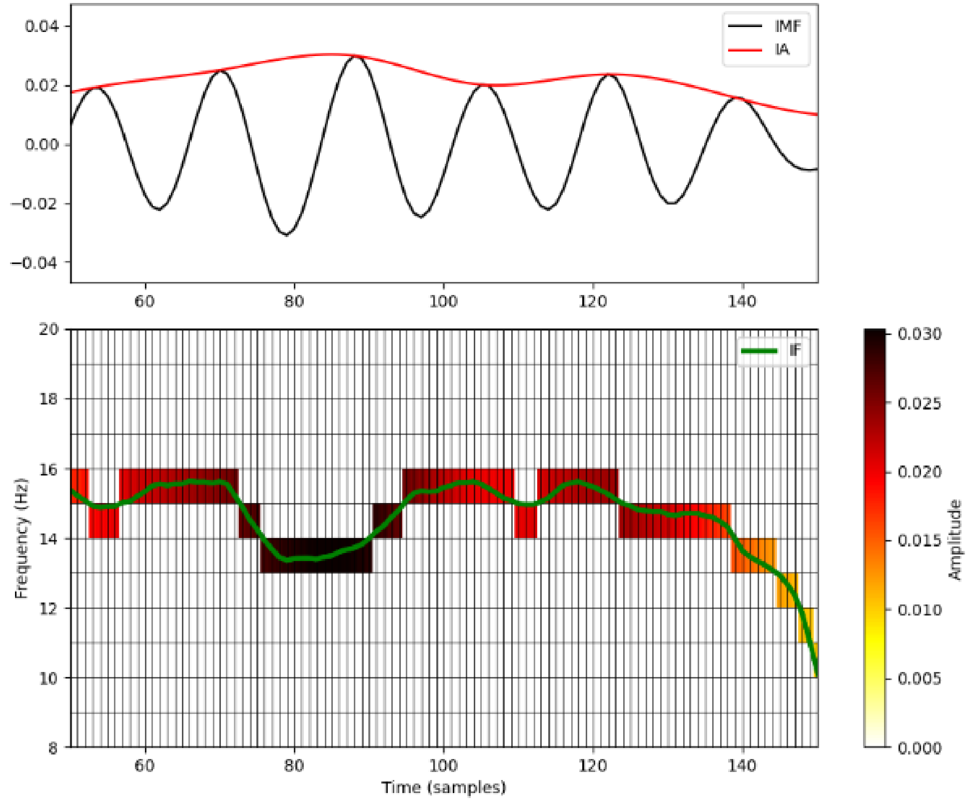




[Andrew J. Quinn et al. (2021) EMD: Empirical Mode Decomposition and Hilbert-Huang Spectral Analyses in Python]

The Hilbert-Huang Transform (HHT)

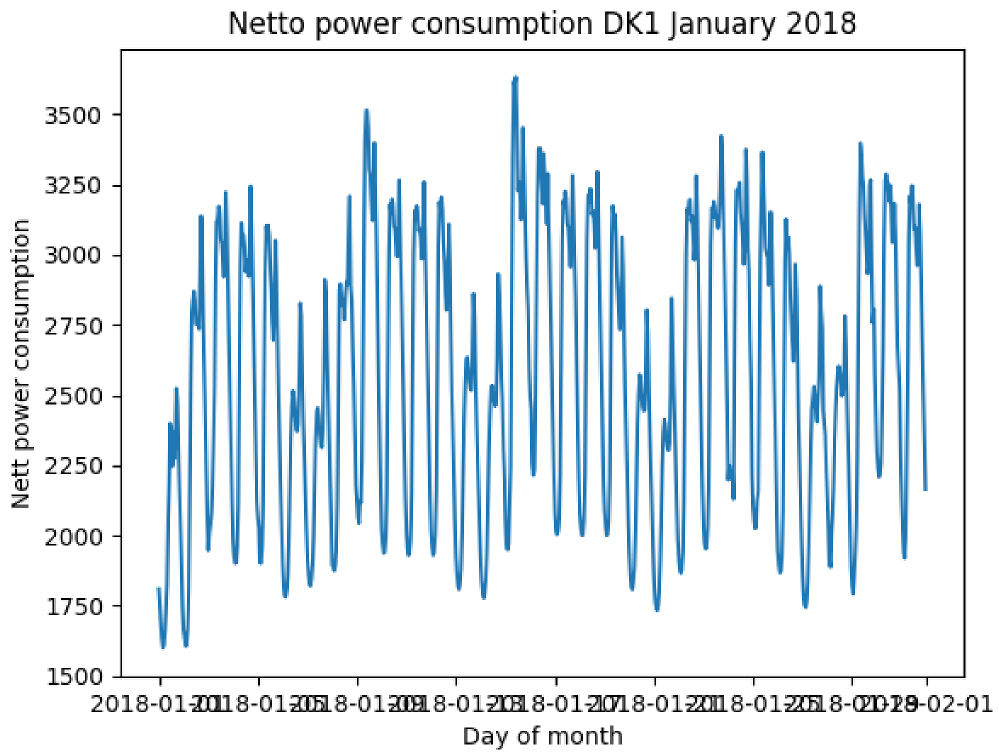
- Provides a description of how the energy or power within a signal is distributed across frequency.
- The distributions are based on the **instantaneous frequency** and **amplitude** of a signal.



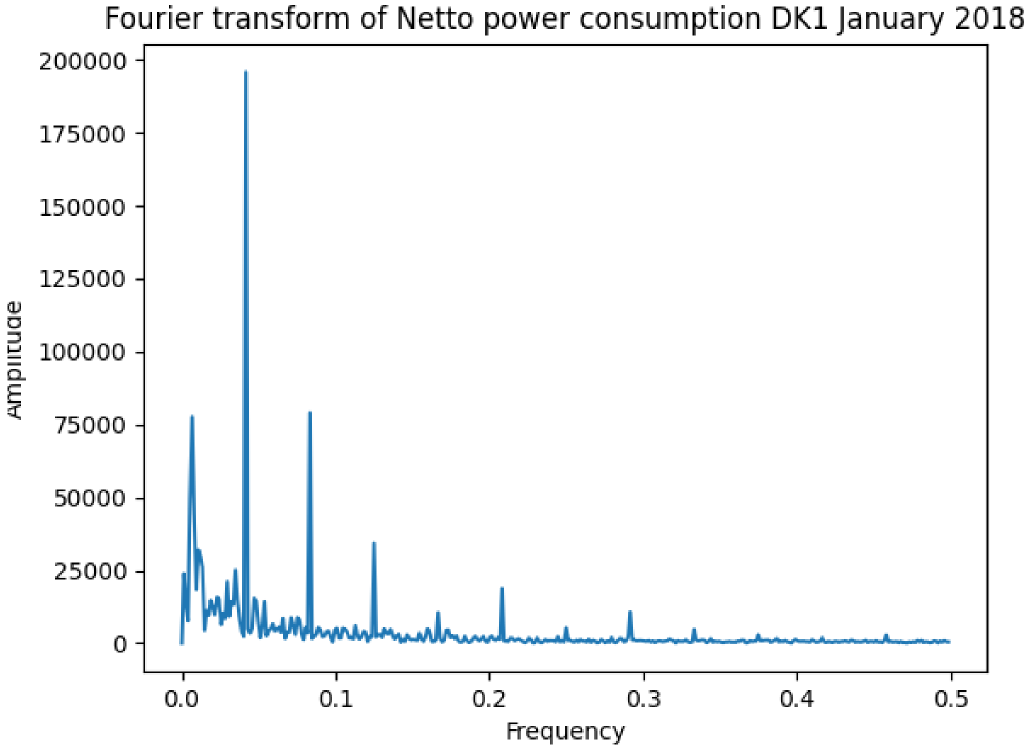
[Andrew J. Quinn et al. (2021) EMD: Empirical Mode Decomposition and Hilbert-Huang Spectral Analyses in Python]

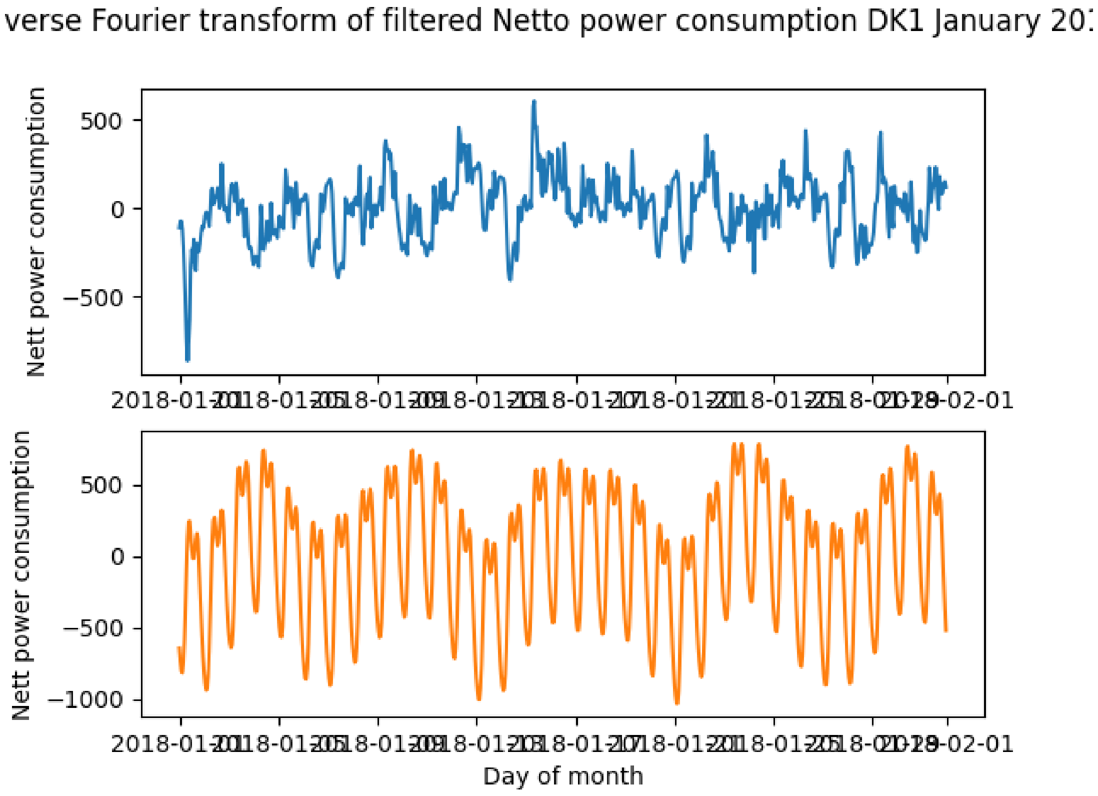
Frequency based methods

- How to handle periodic signals
- Same seasonal trends over whole signal, wide sense stationarity
- Remember to remove median

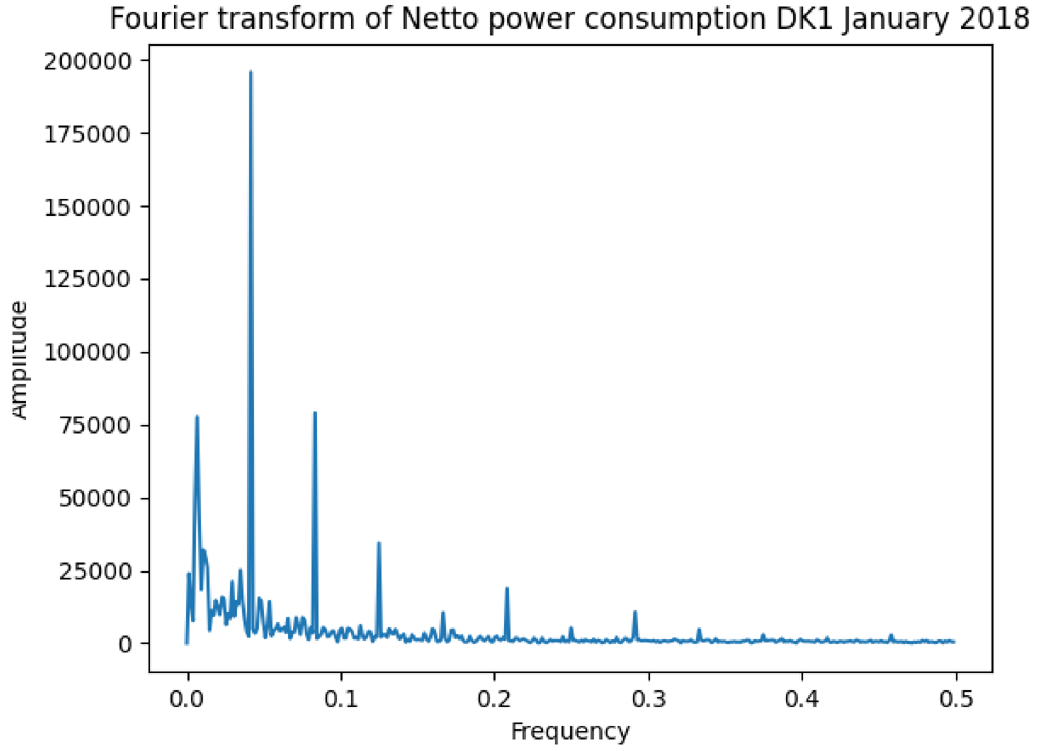


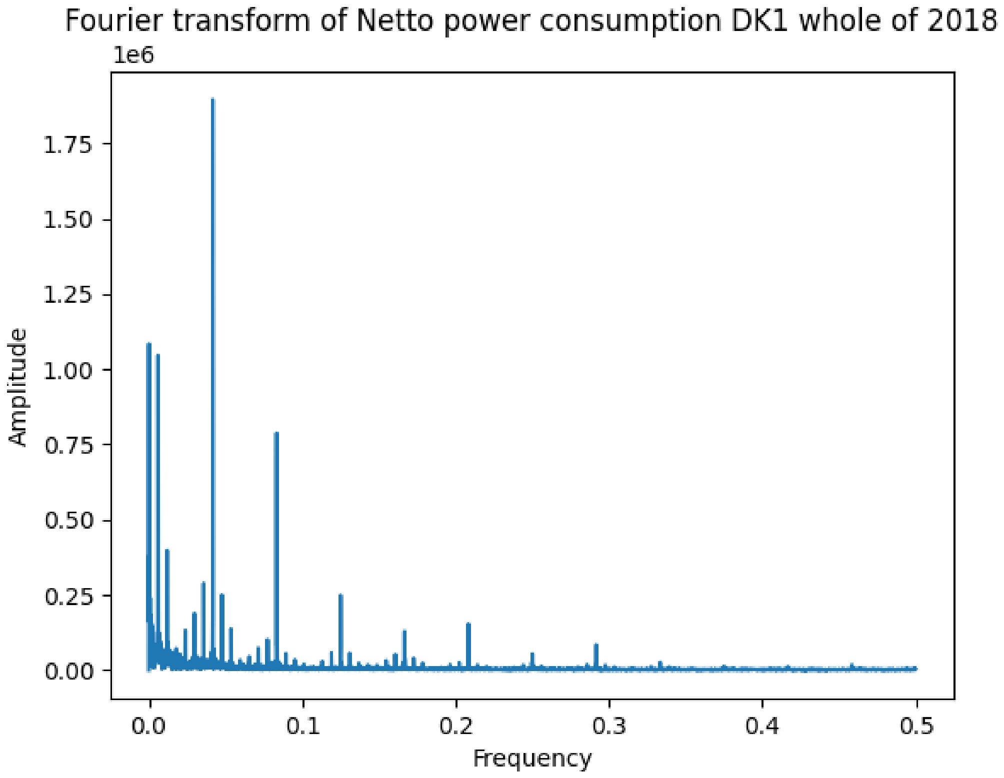
Filtering in Fourier domain



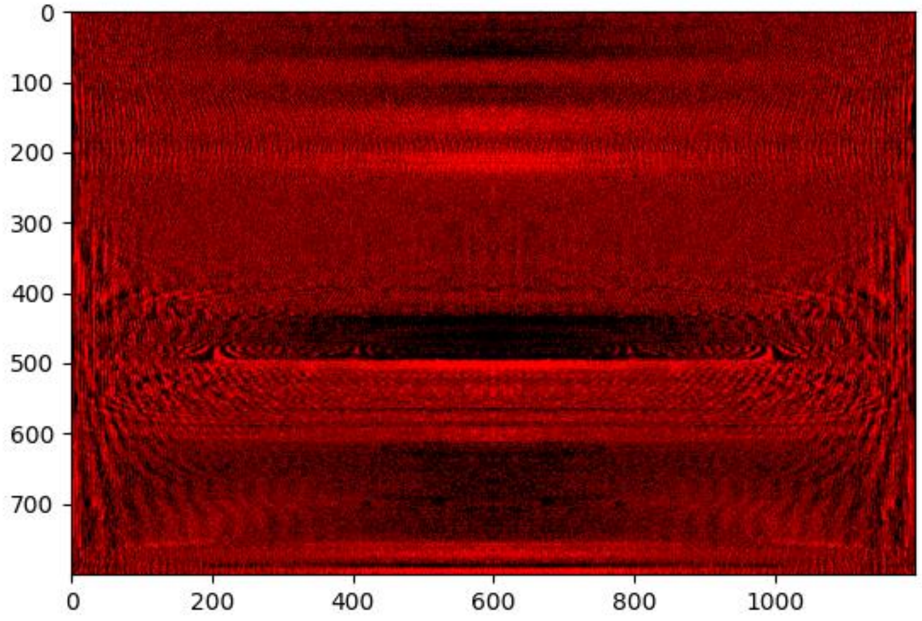


Longer data -> better spectra



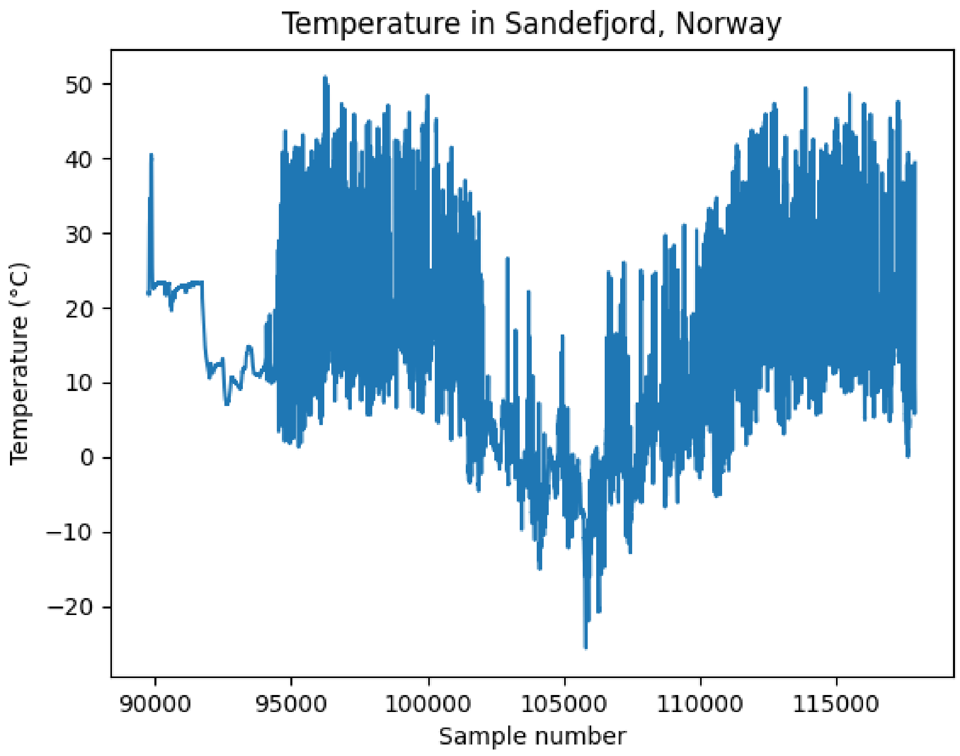


Works in all dimensions

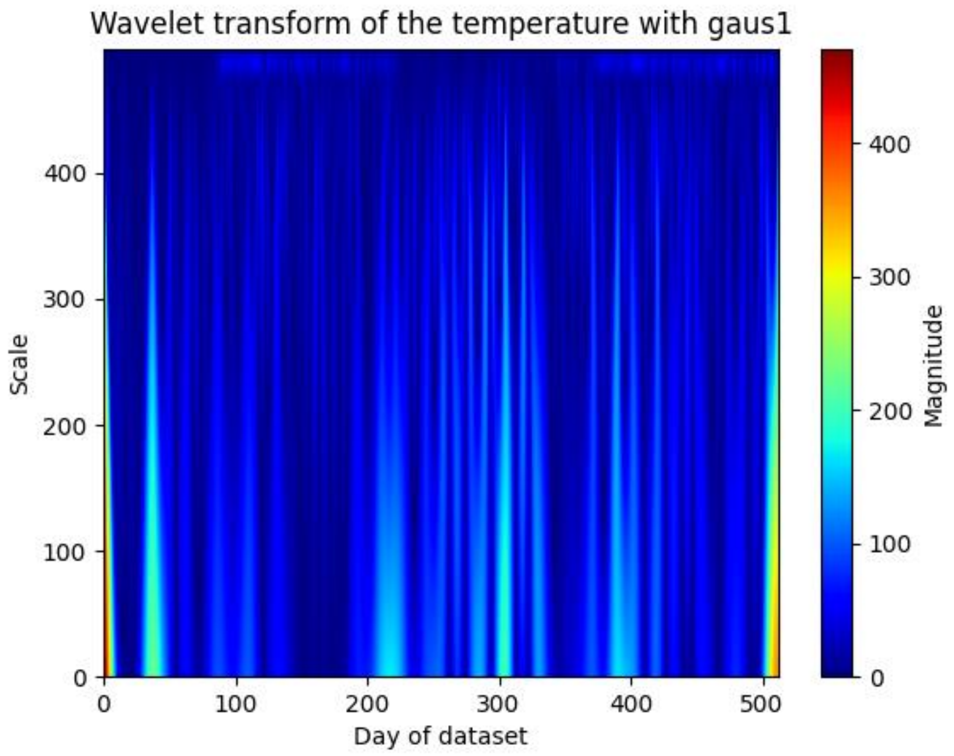


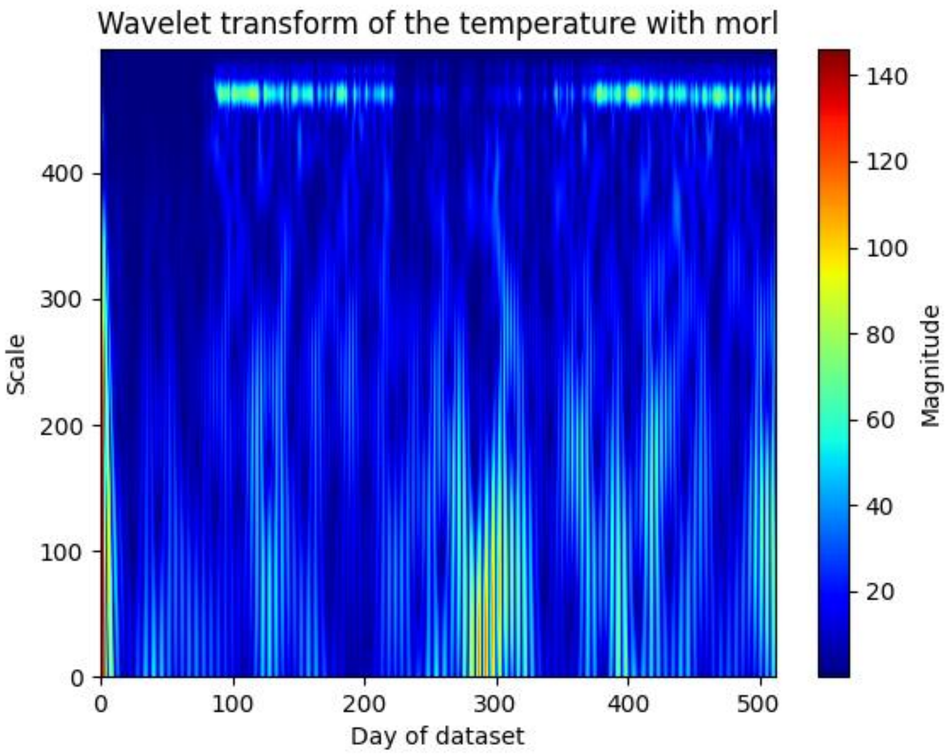
Non-stationary signals

- Some time variation
- Fourier transform doesn't show time
- Wavelet transform fixes this

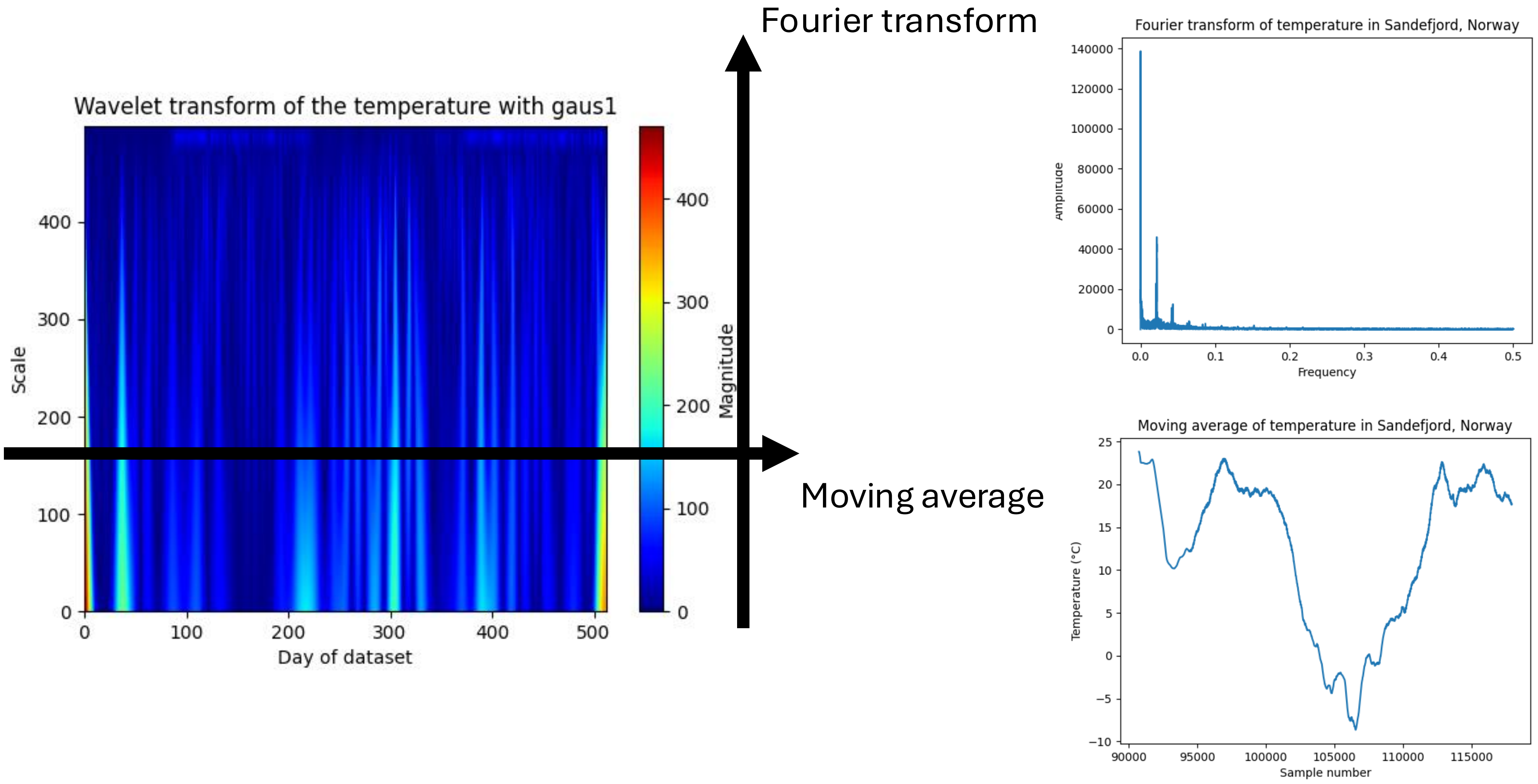


Wavelet transform





Connection with other methods



In conclusion

- Infinite decomposition algorithms exists
- Prior and domain knowledge is key
- It is worth trying multiple methods