

Time Series Analysis

INFO 523 - Lecture 12

Dr. Greg Chism

Lesson 2: Processing Timeseries Data

Lagging Values

- While analyzing time series, we often refer to values that our time series took **1, 2, 3**, etc., time steps in the past
- These are known as lagged values and denoted:

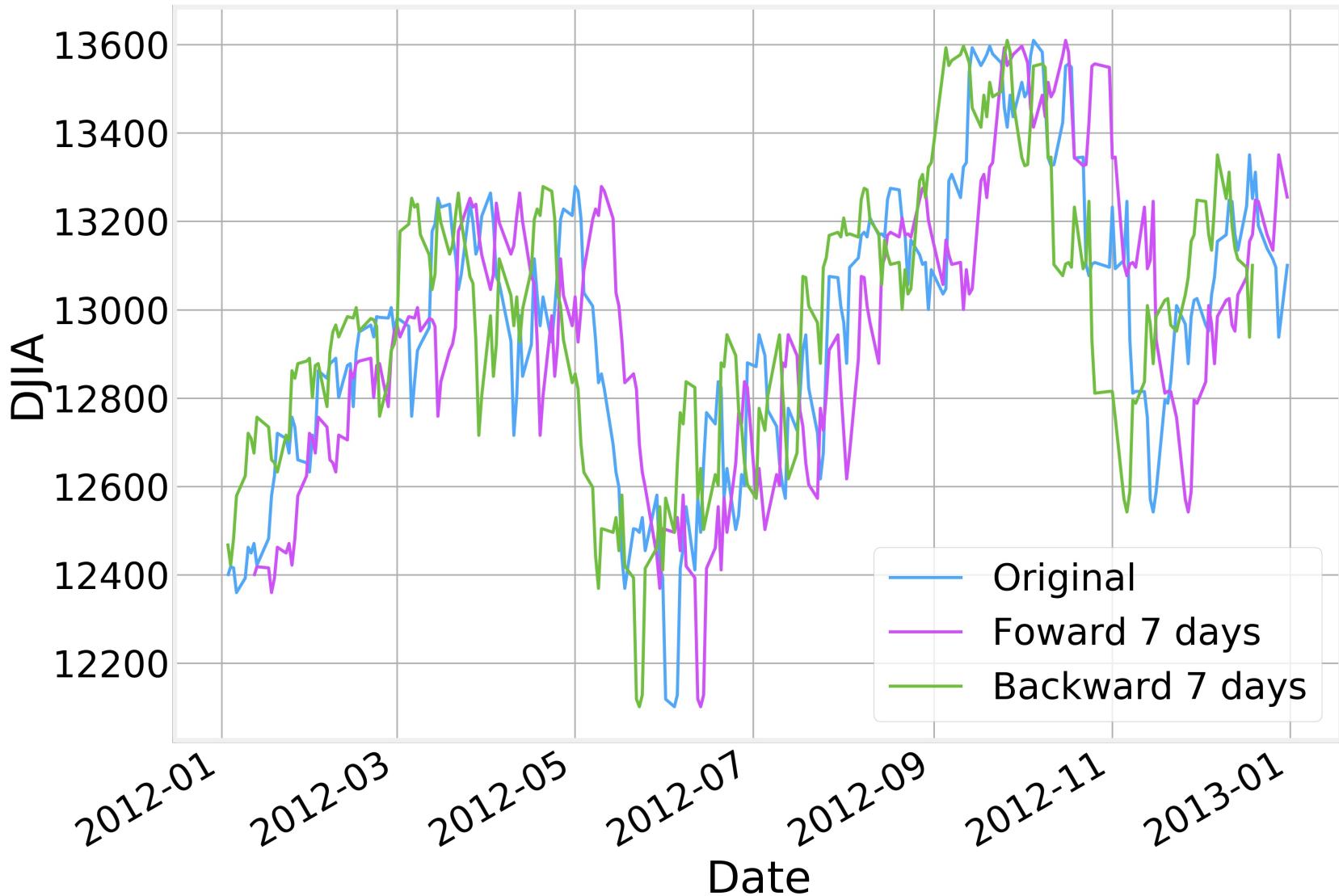
$$X_{t-l}$$

- where ***l*** is the value of the lag we are considering.

Lagging Values



Lagging Values



Differences

- Perhaps the most common use case for lagged values is for the calculation of **differences** of the form:

$$X_t - X_{t-l}$$

- Where $l \geq 1$ is the value of the lag we are interested in.
- Naturally, higher order differences can also be used, in which case, the difference of the difference is calculated:

$$y_t = X_t - X_{t-l}$$

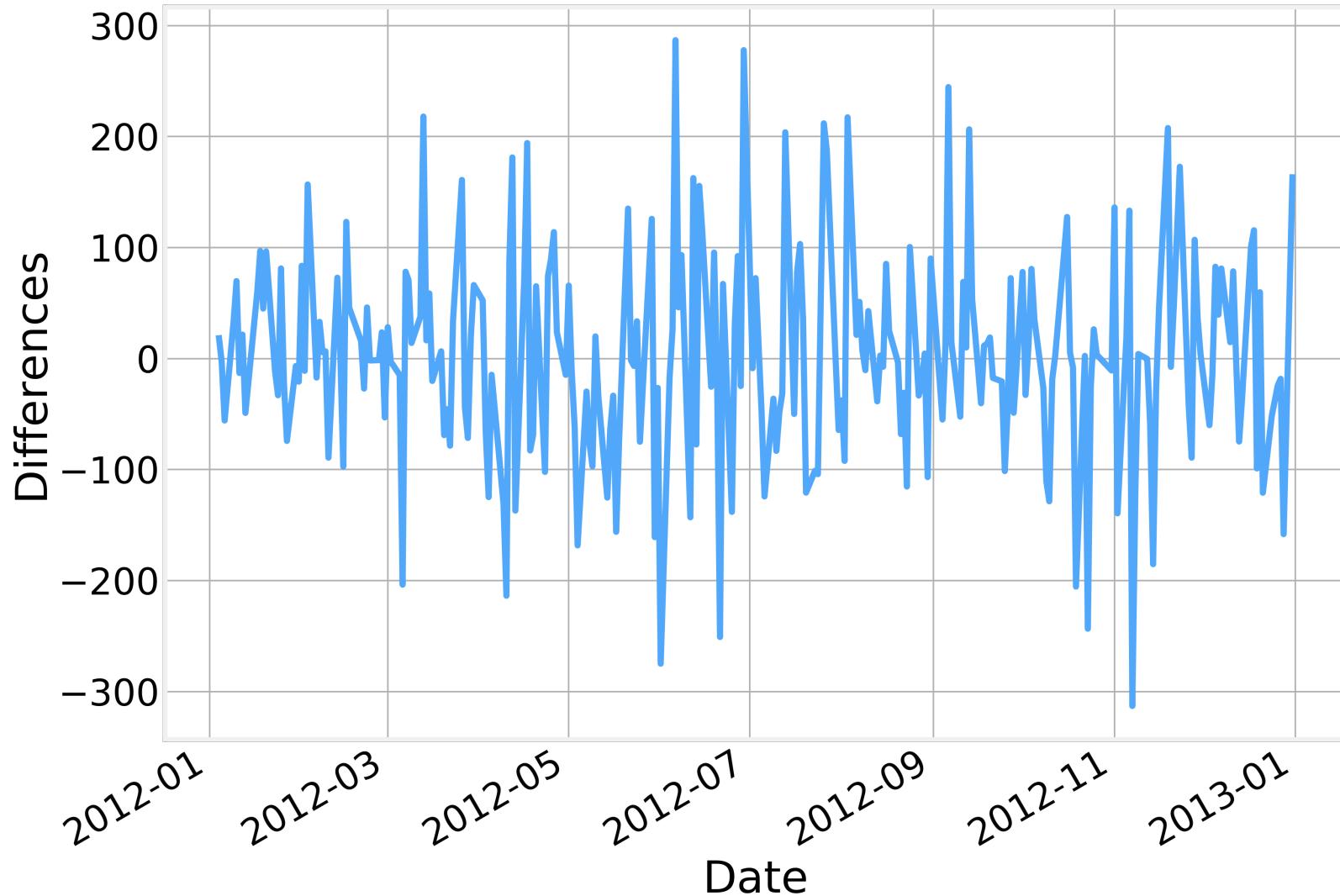
$$z_t = y_t - y_{t-l} \equiv X_t - 2X_{t-l} + X_{t-2l}$$

- This can be thought of as a discrete version of the usual derivative of a function.
- Differences are also a particularly simple way to **detrend** a time series

Differences



Differences



Windowing

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Windowing

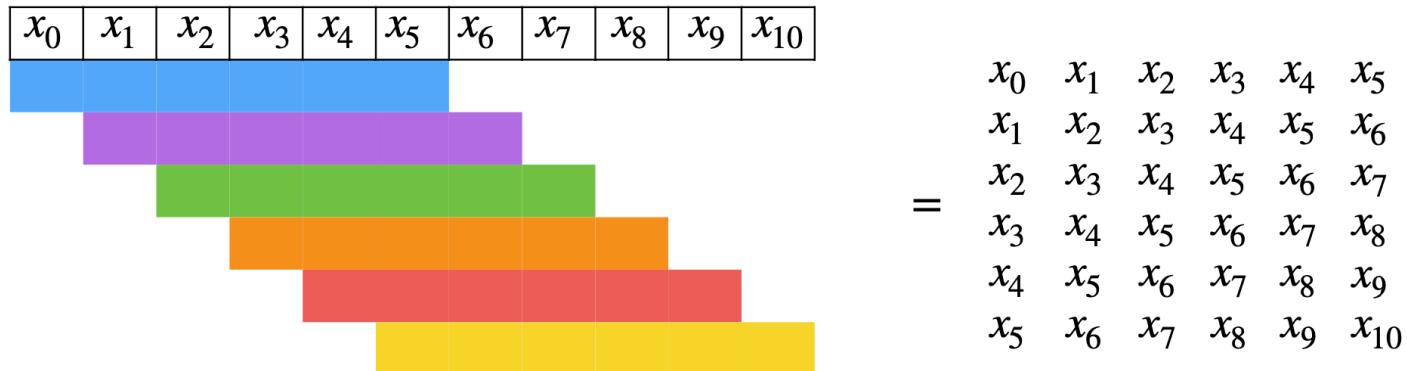
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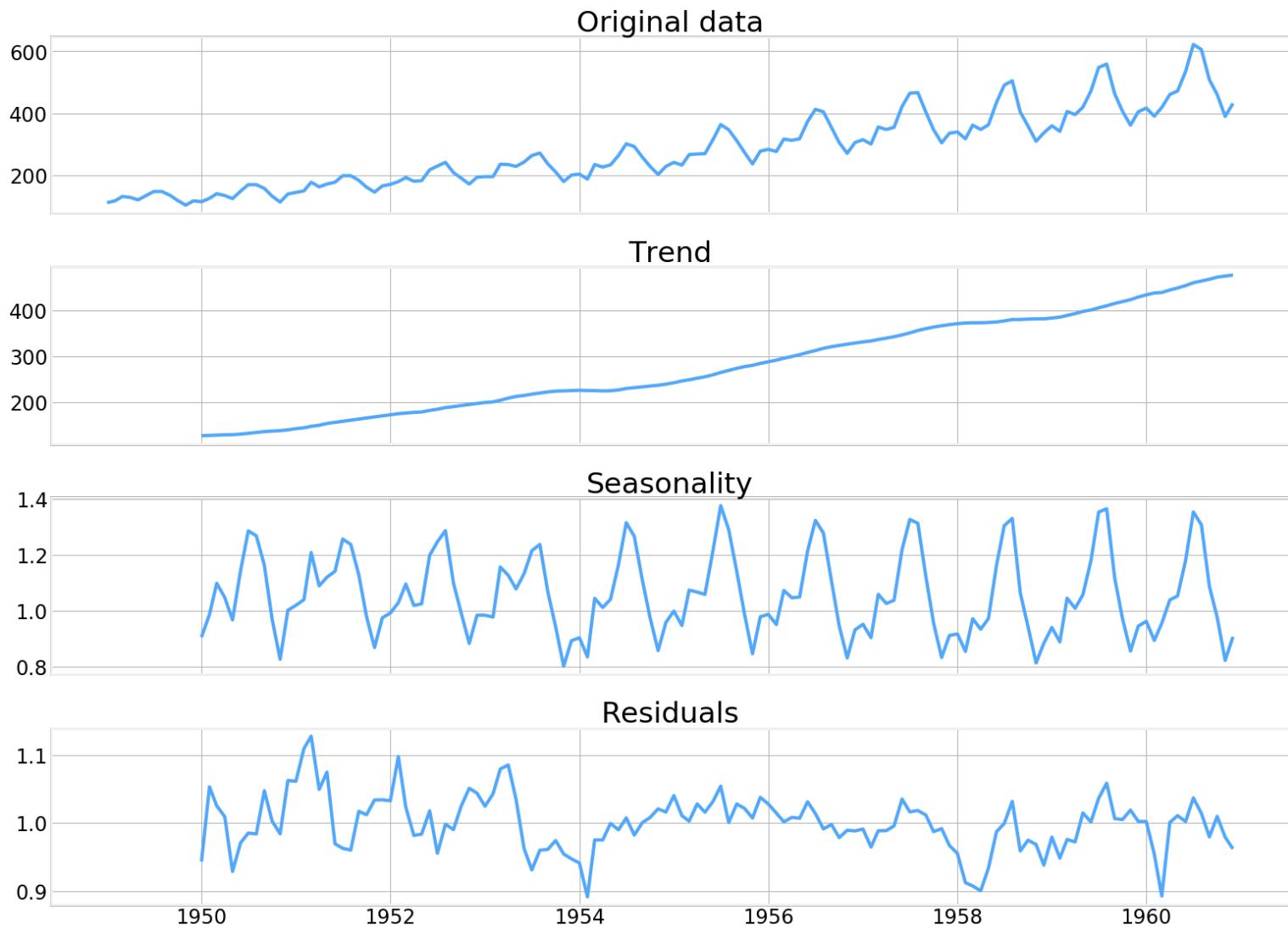
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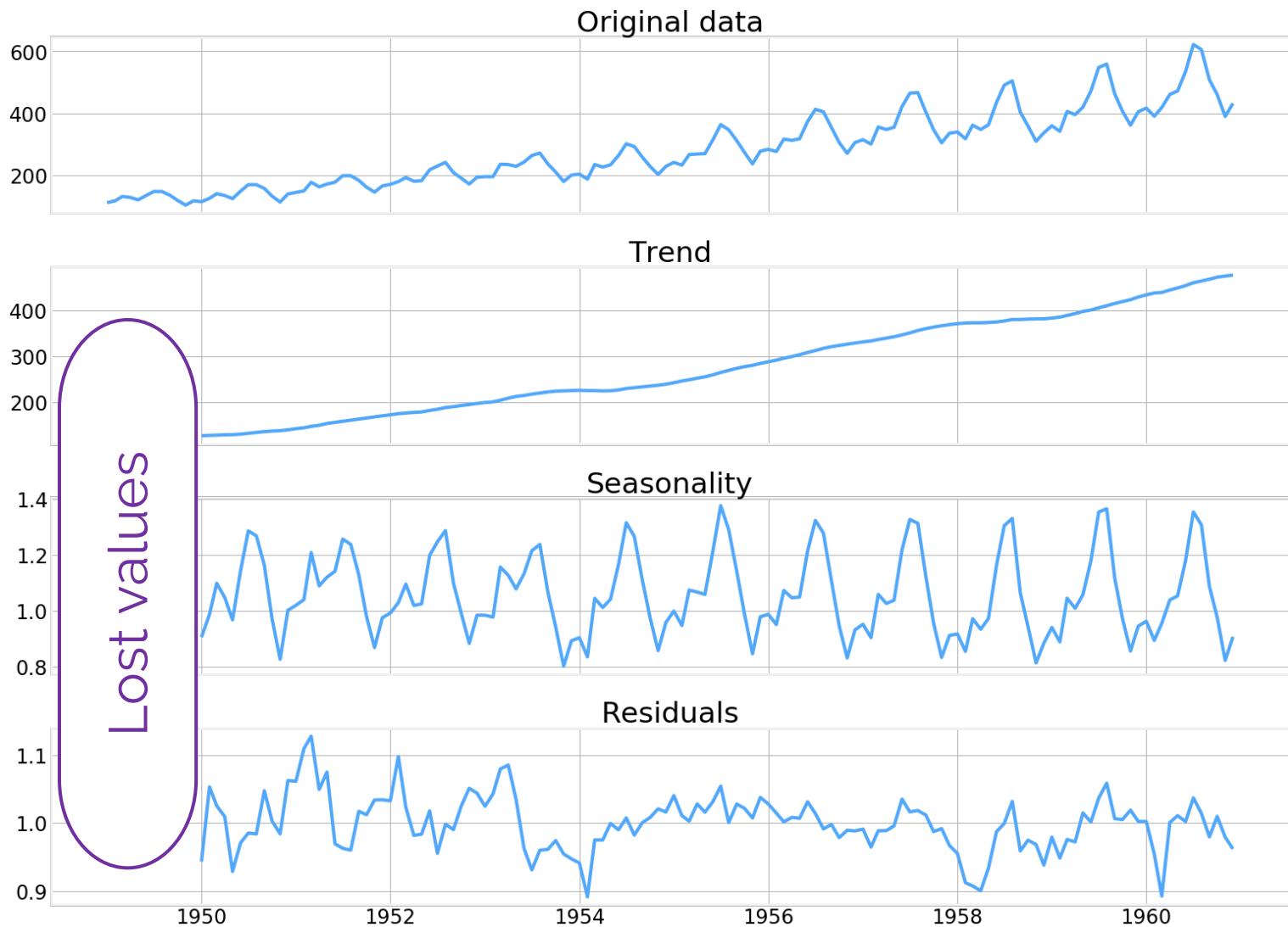
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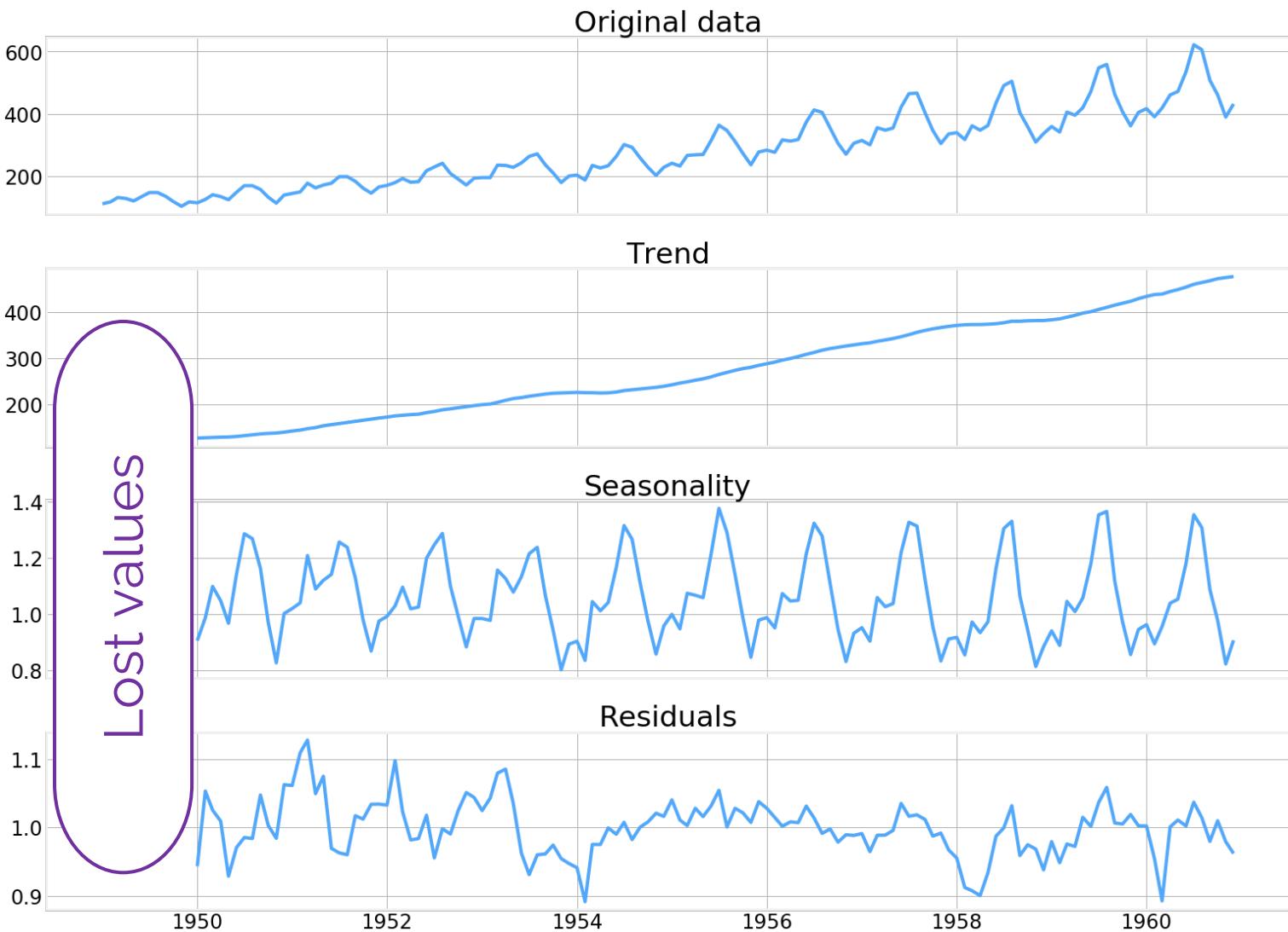


Windowing



Windowing

One common approach is to place all "lost values" at the beginning as it avoids "future leaking" when splitting the dataset



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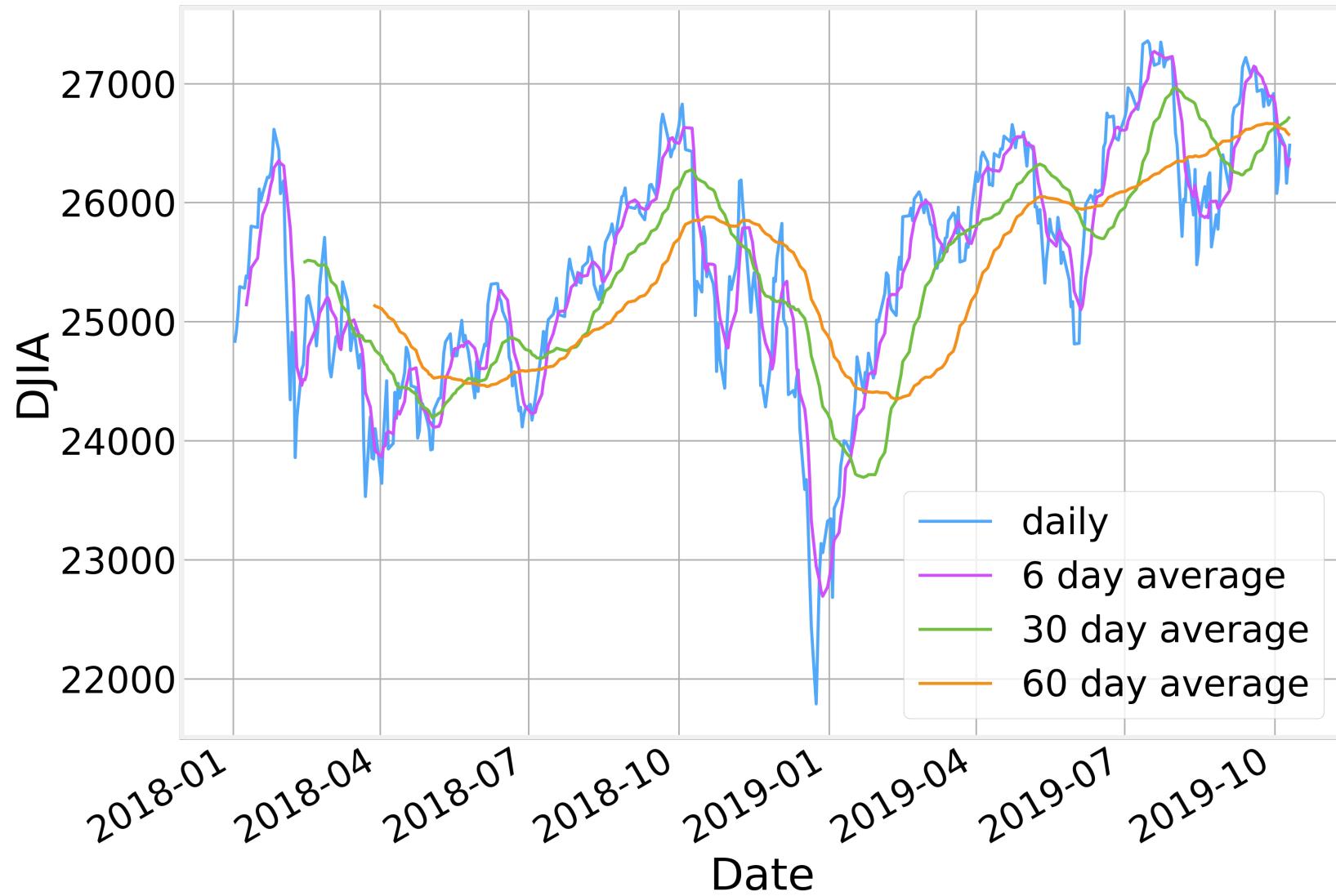
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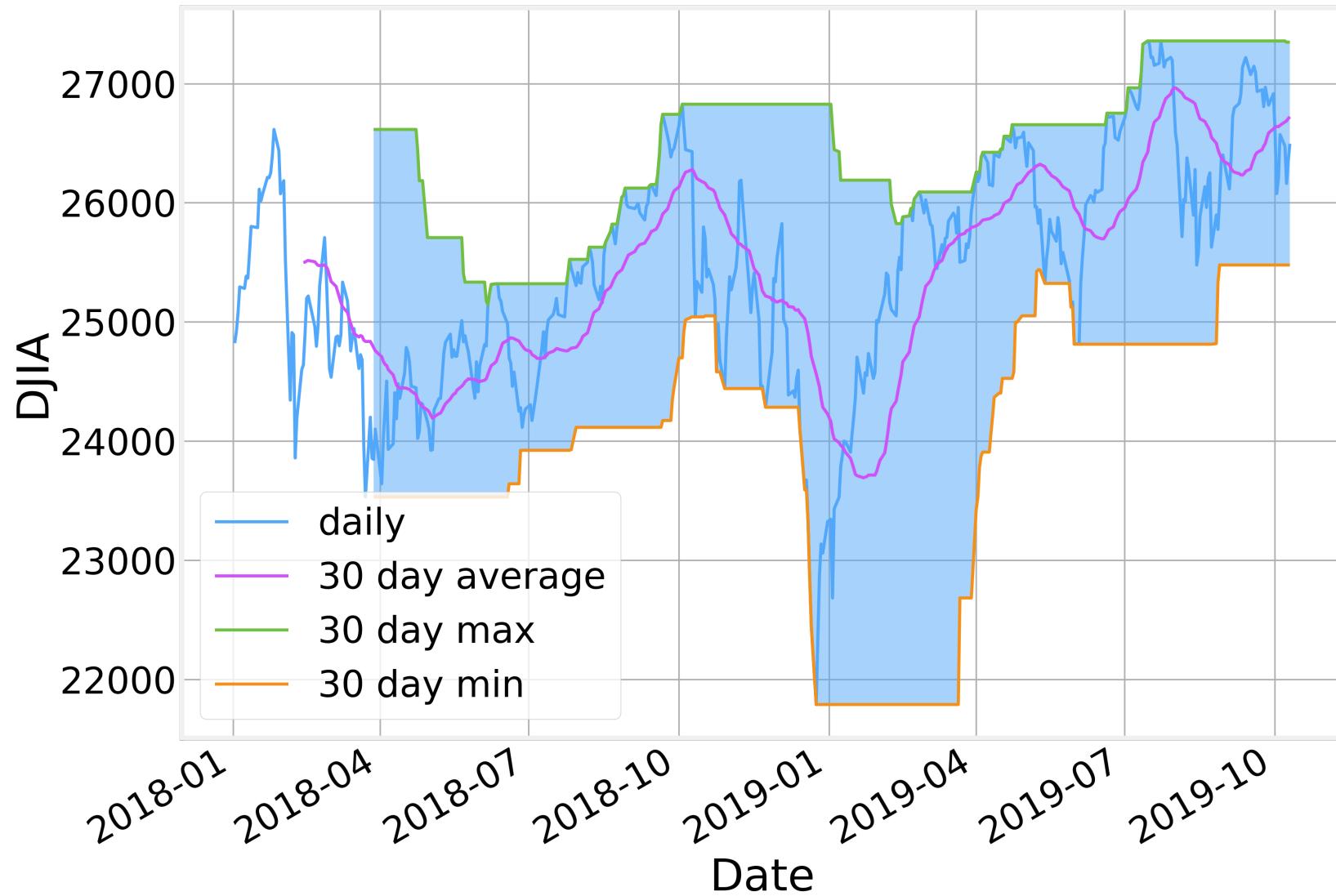
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- Depending on the application we can choose to place the missing values in either or (or even both) extremes of the time interval

Running Values



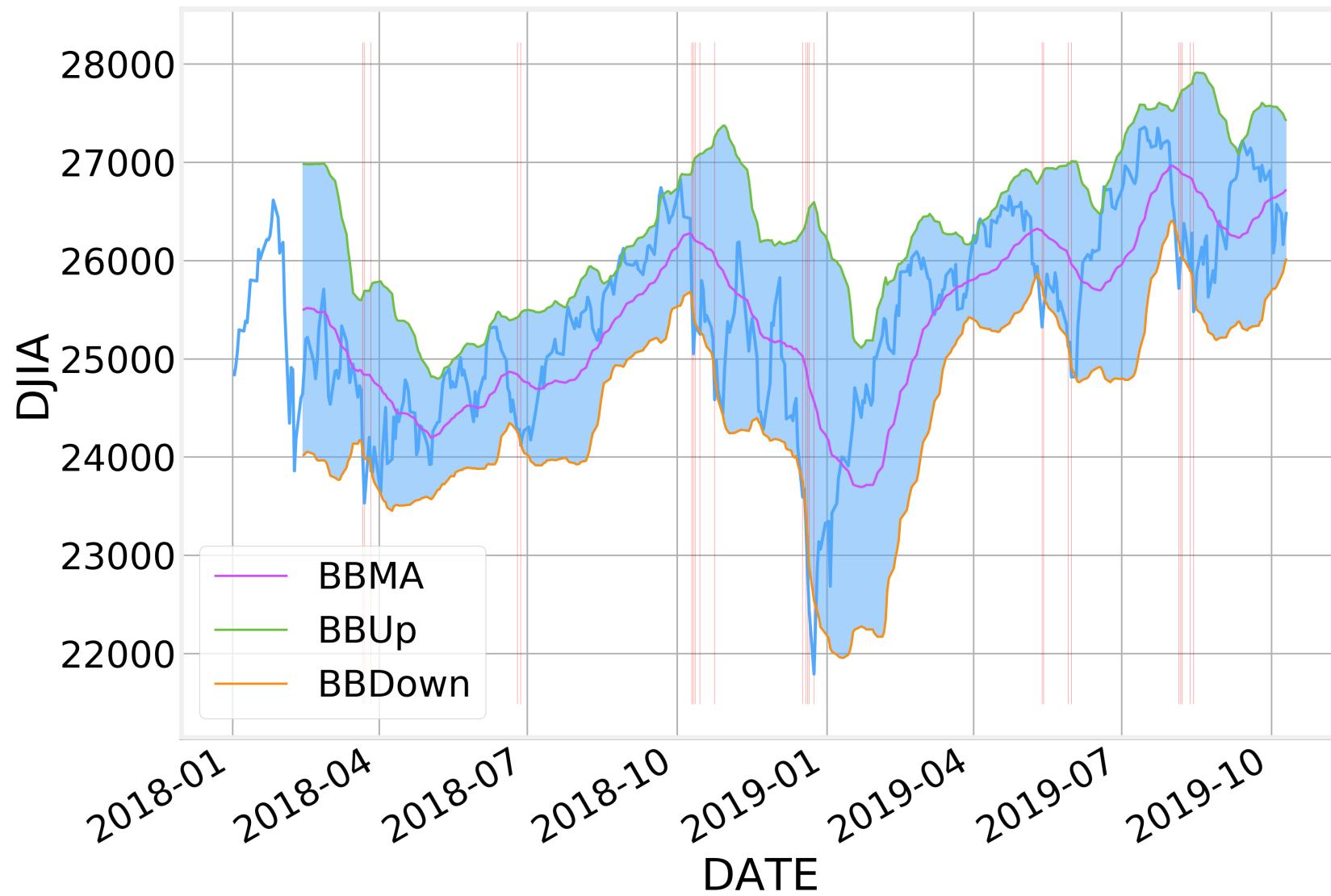
Envelopes



Bollinger Bands

- A common use for application for running values is the calculation of **Bollinger Bands**.
- Introduced by [John Bollinger](#) in the 1980s as a complement to more traditional time series technical analysis techniques.
- **Bollinger Bands** are defined by two components:
 - A N period moving average, μ_N
 - The area K standard deviations above and below the moving average $\mu_N \pm K\sigma_N$
- Both μ_N and σ_N are computed on a [running window](#) of size N
- The values N and K are application specific. For stock trading, $N=20$ and $K=2$
- Whenever the time series steps out of the Bollinger Band that's a clear indication of a **change in the temporal behavior**.

Bollinger Bands



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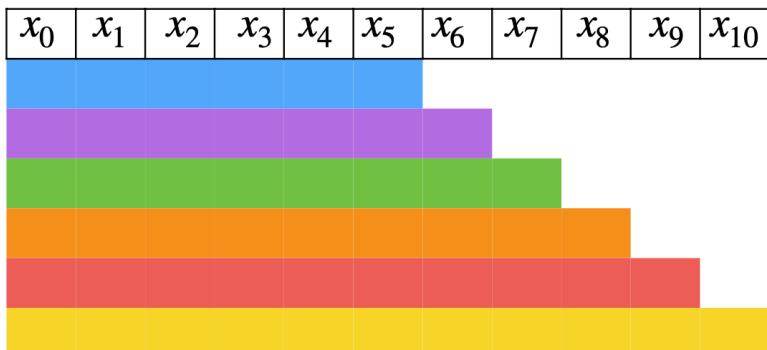
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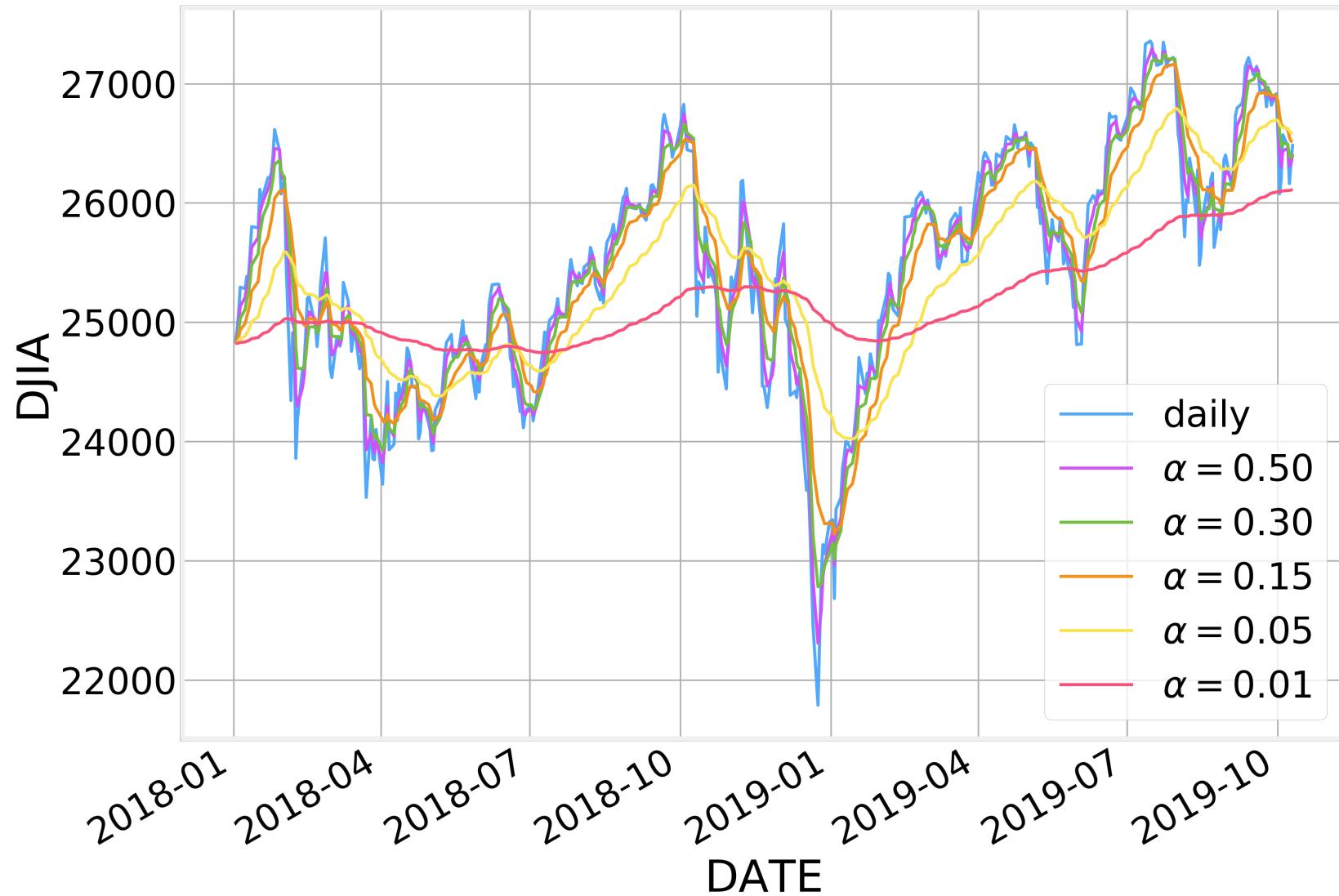
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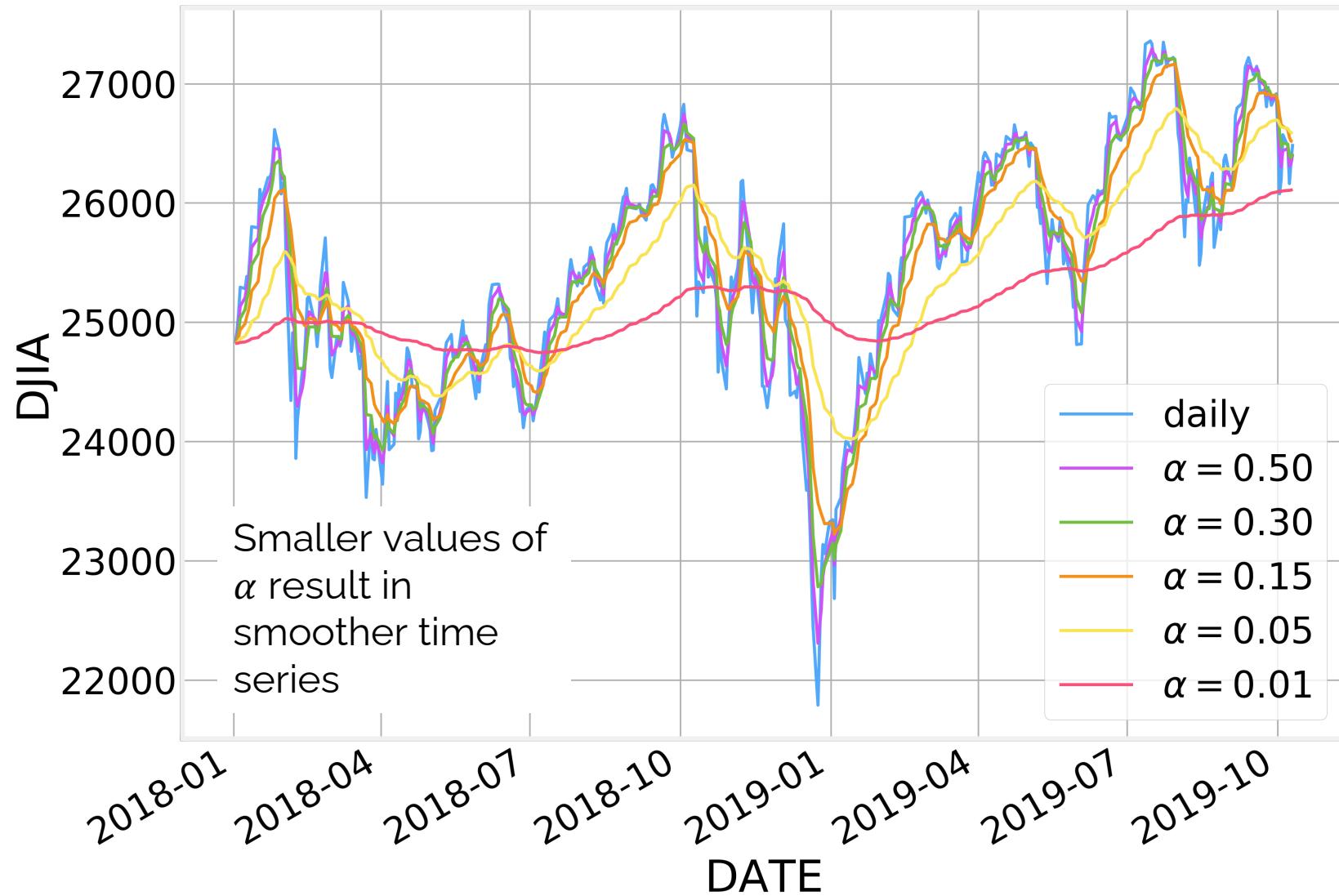


$$\begin{pmatrix} \alpha & & & & & & & & & \\ \alpha(1-\alpha)^1 & \alpha & & & & & & & & \\ \alpha(1-\alpha)^2 & \alpha(1-\alpha)^1 & \alpha & & & & & & & \\ \vdots & \vdots & \vdots & \ddots & & & & & & \\ \alpha(1-\alpha)^{n-1} & \alpha(1-\alpha)^{n-2} & \alpha(1-\alpha)^{n-3} & \ddots & \alpha & & & & & \end{pmatrix}$$

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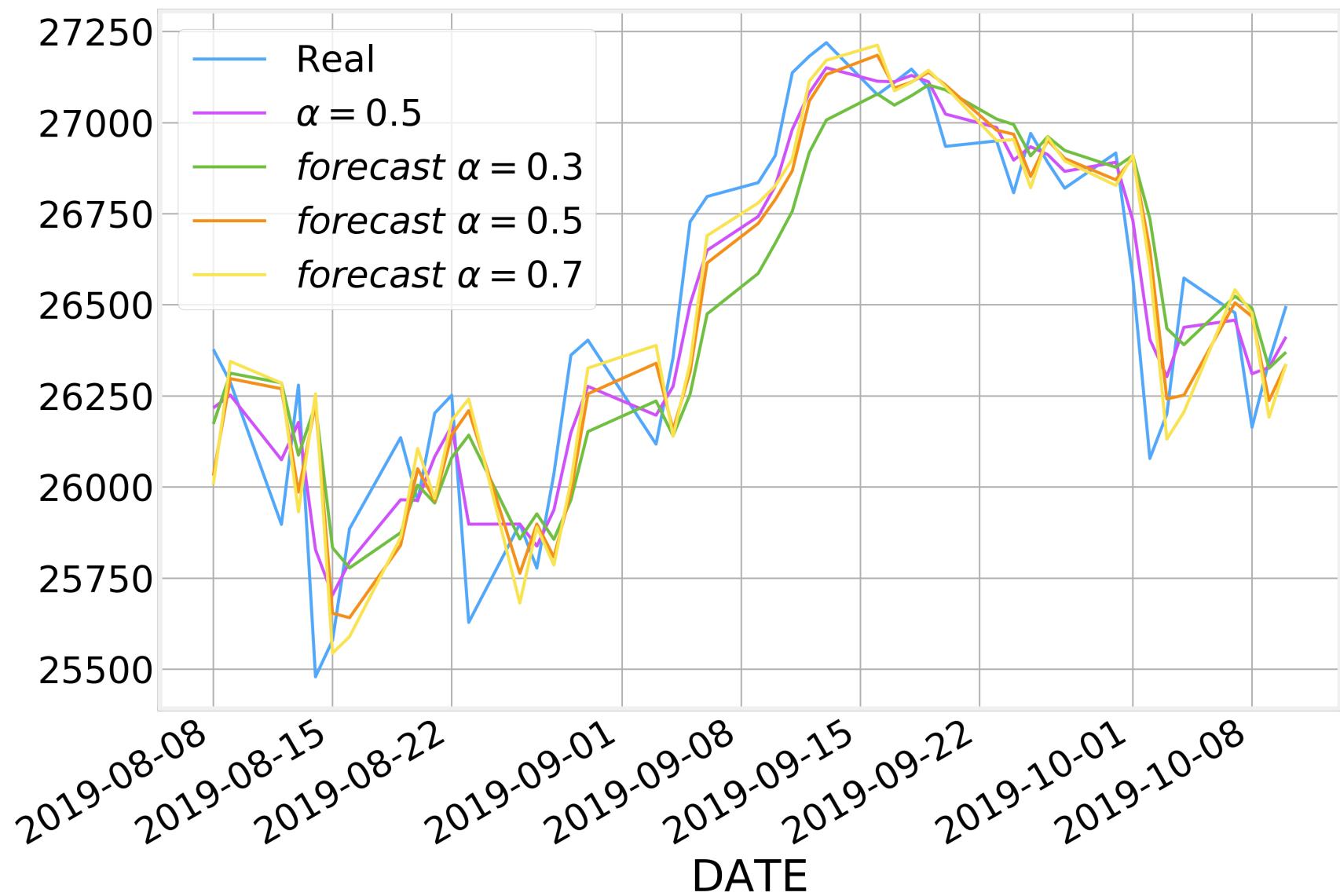
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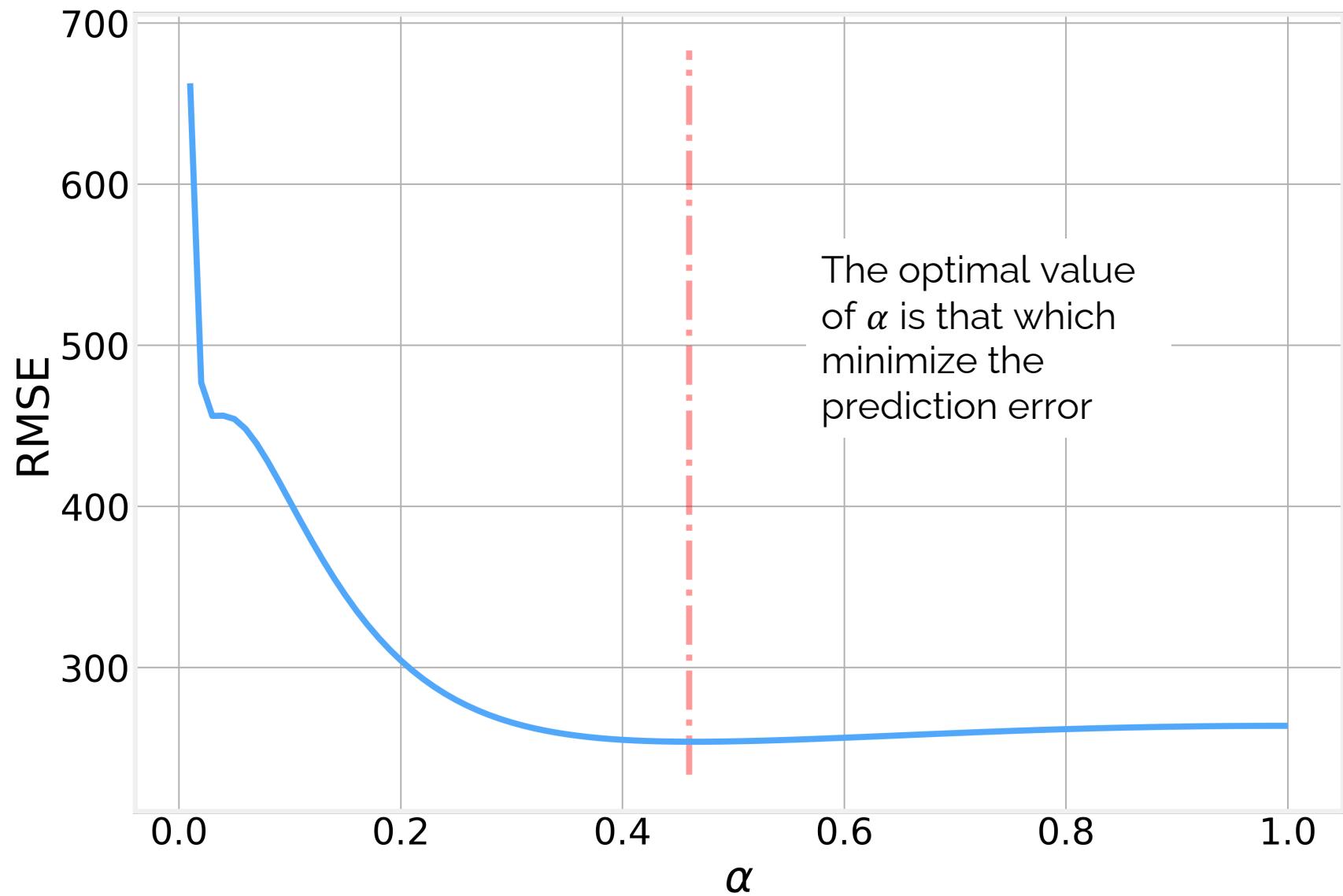
- Which we can consider to be a prediction on the value of x_{t+1} , based on the current value of z_t and some factor of our current error value $x_t - z_t$:

$$z_{t+1} = z_t + \alpha(x_t - z_t)$$

Forecasting

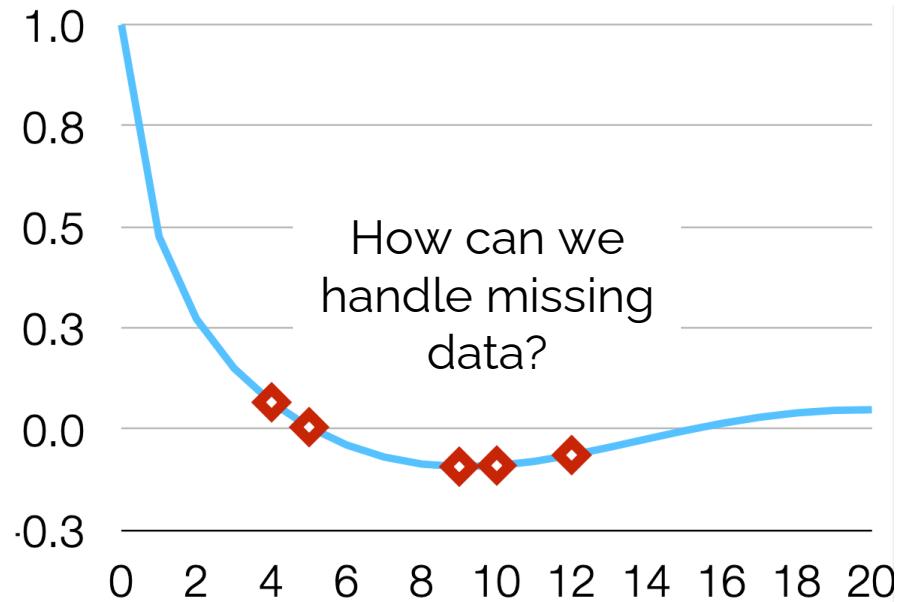


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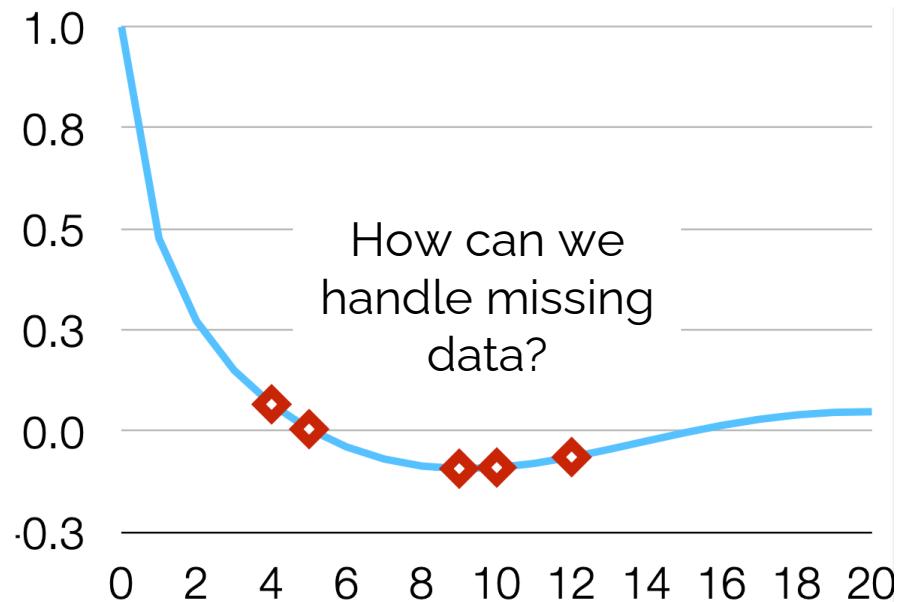
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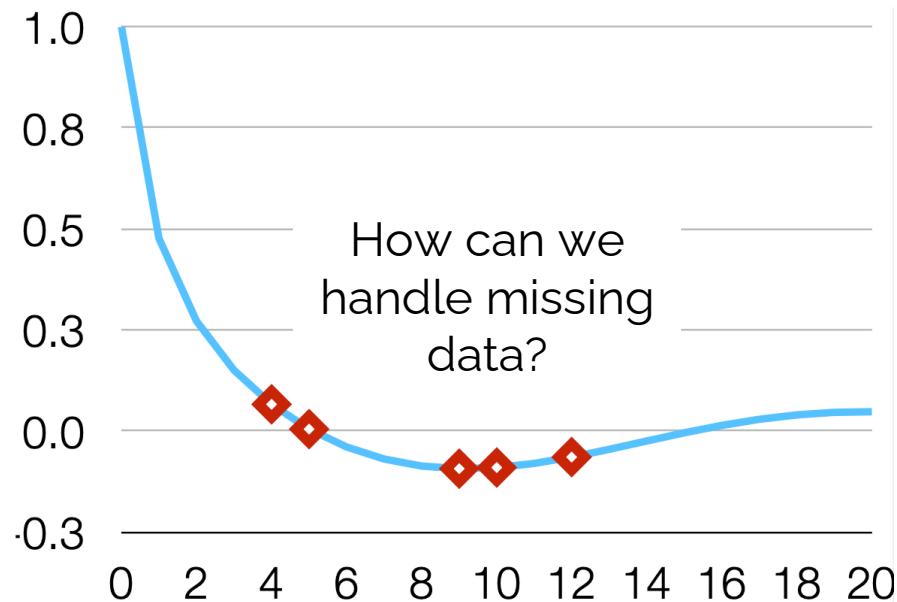
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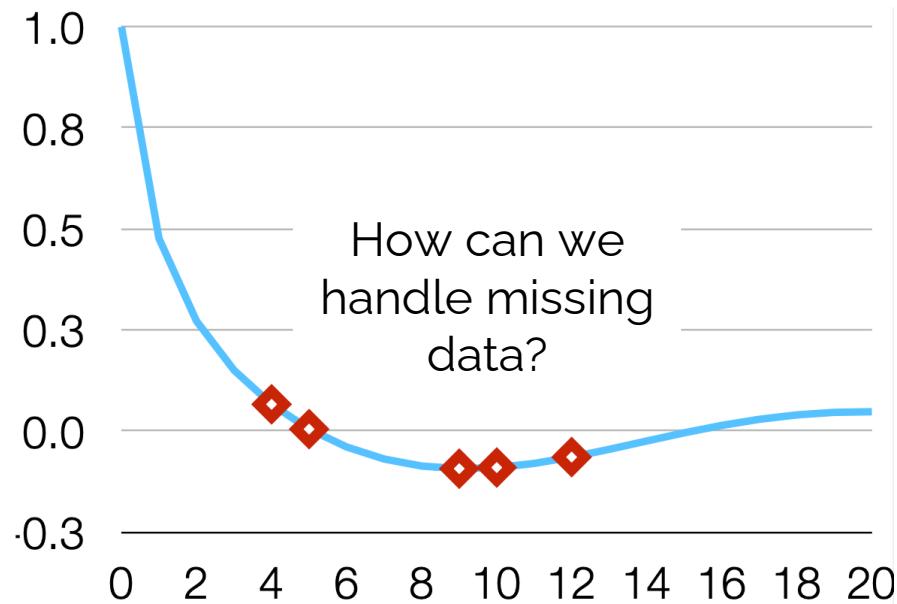
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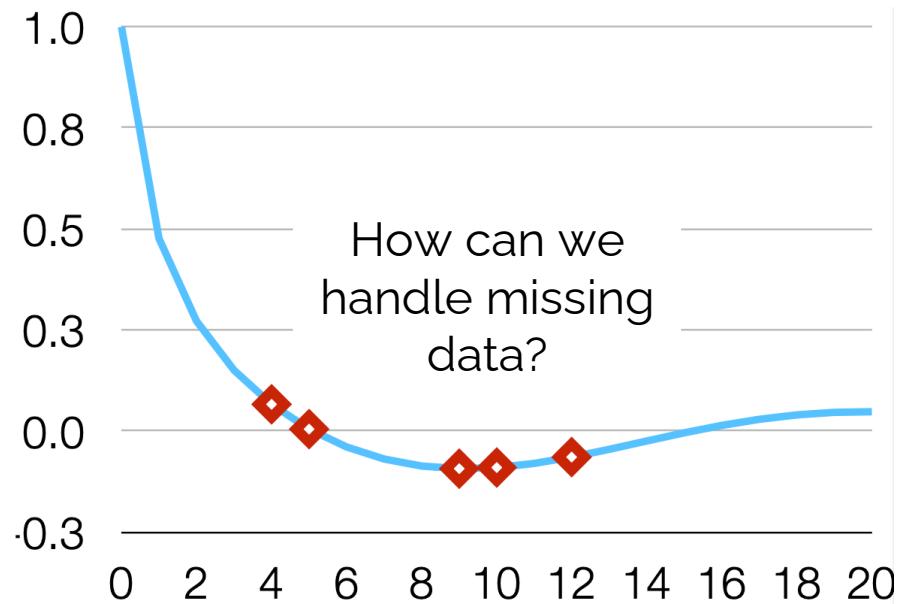
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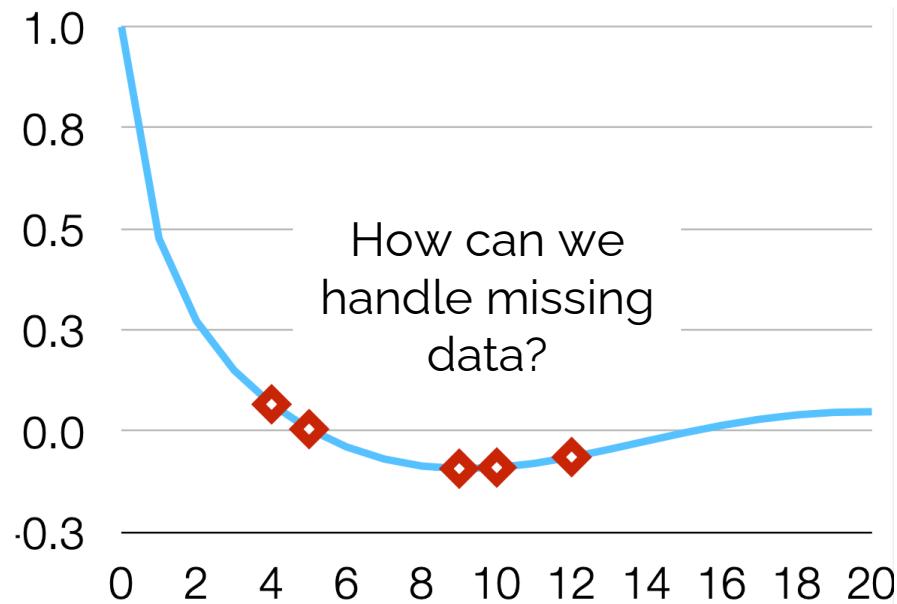
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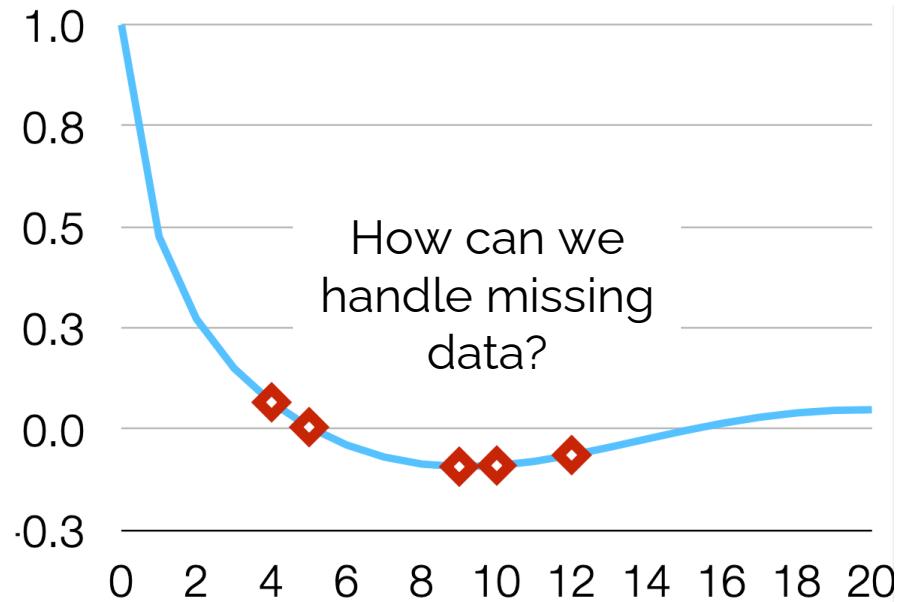
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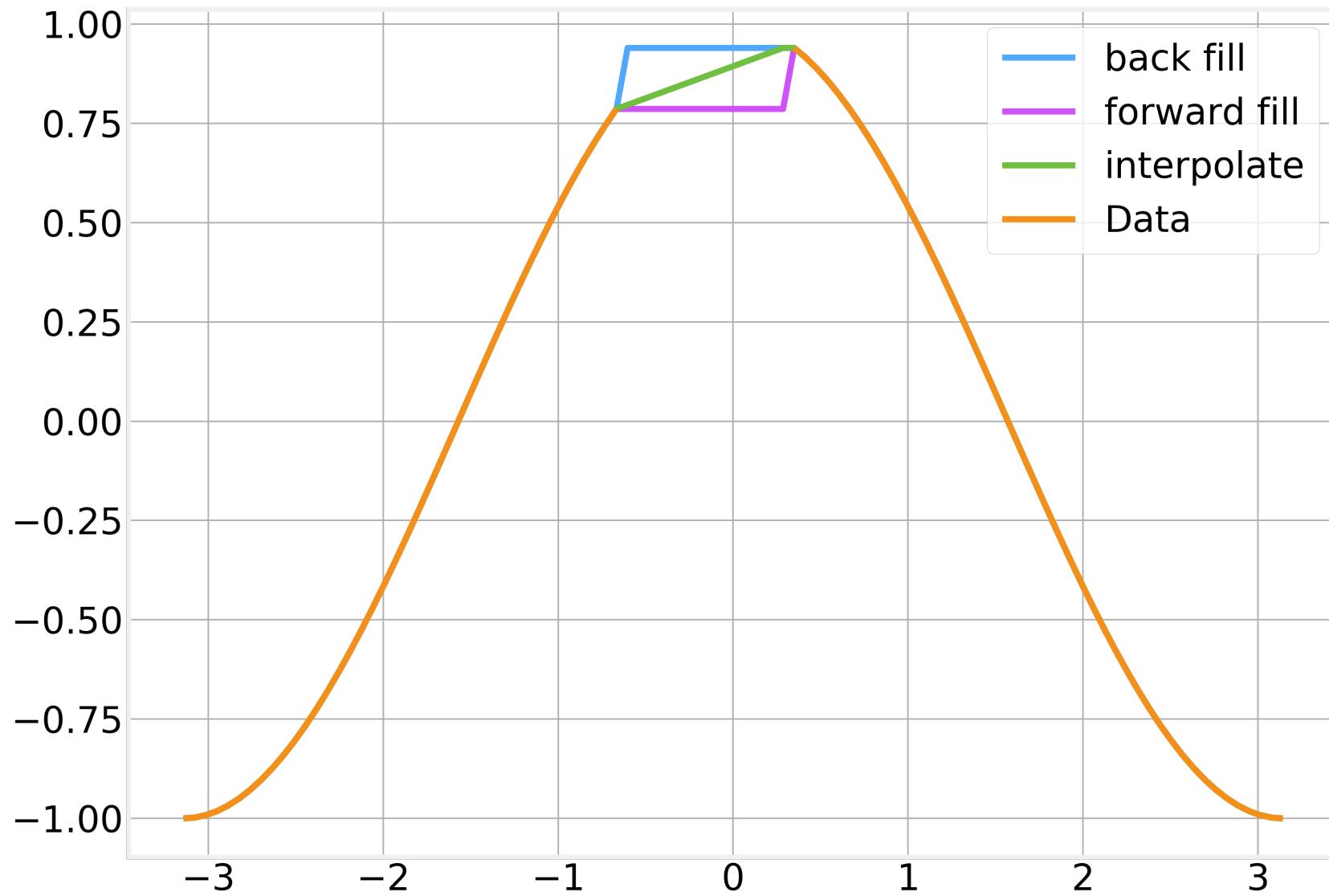


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 - **imputation** – add values based on what we expect the missing values to be



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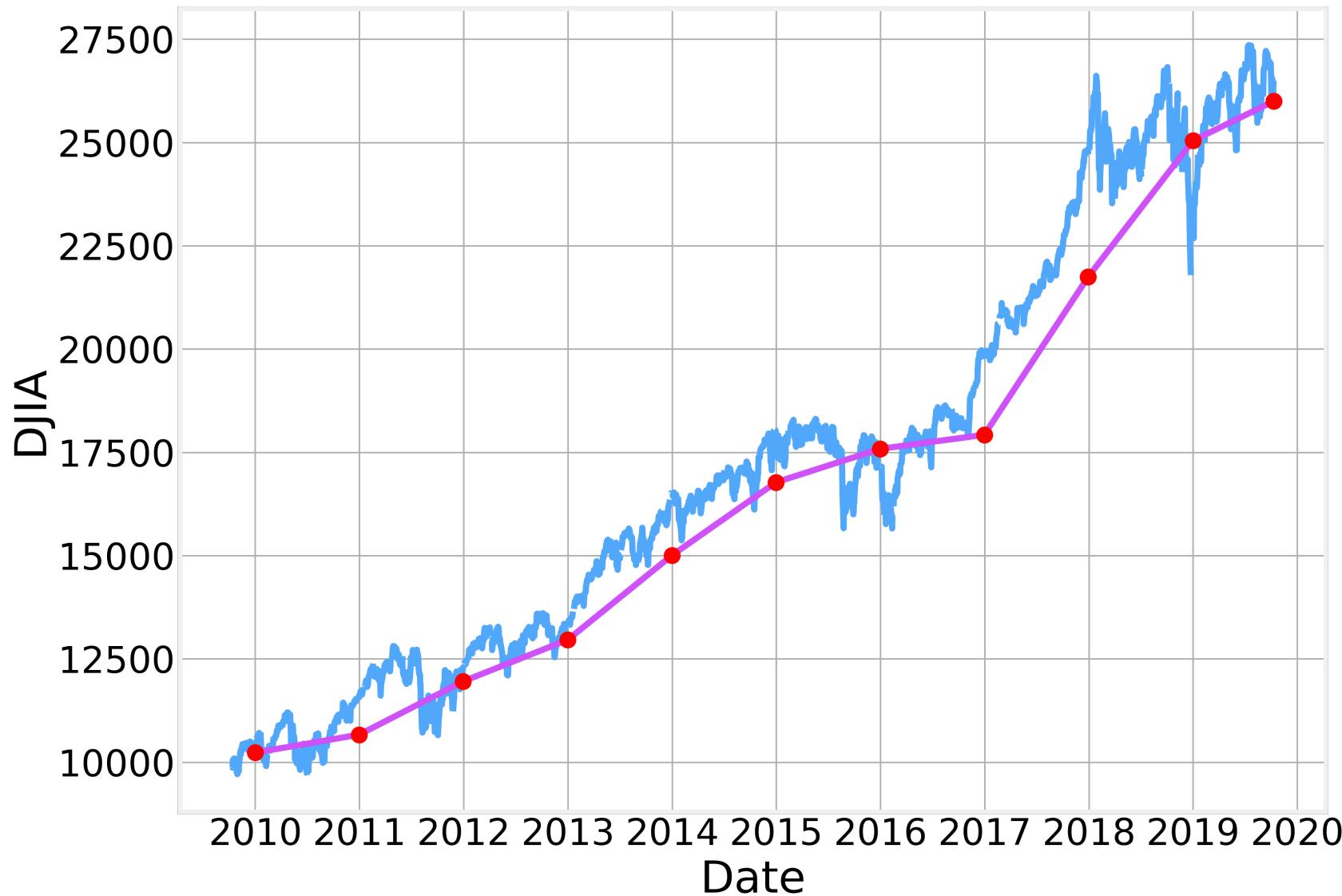
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 - Going from weekly to daily frequency requires specifying how to allocate the values for each day of the week

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