# Box Cox transform: Guerrero method

Time series decomposition

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BOX COX TRANSFORM

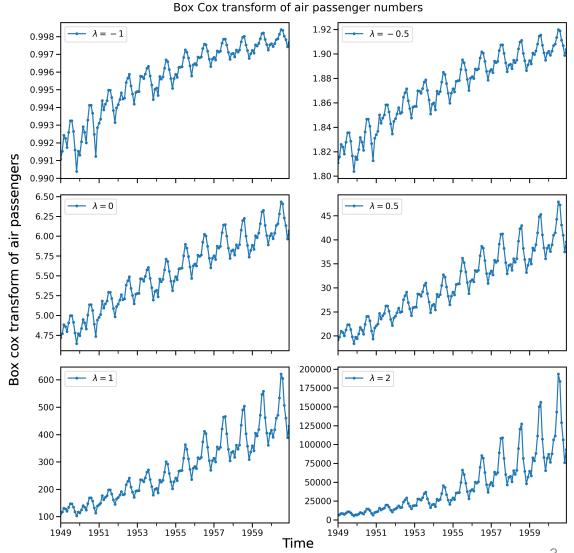
GUERRERO METHOD TO SELECT LAMBDA

# **Box Cox recap**

- Some forecasting & decomposition methods perform better if the variance of the time series does not change with the level of the time series (e.g., ARIMA).
- The Box Cox transform is defined as:

$$y^{(\lambda)} = \frac{y^{\lambda} - 1}{\lambda};$$
 if  $\lambda \neq 0$   
= log(y); if  $\lambda = 0$ 

- Different values of  $\lambda$  correspond to different kinds of transforms.
- How do we pick a good value for λ?



### Coefficient of variation

- The coefficient of variation is a scaled measure of variability of a dataset.
- Coefficient of variation:

$$C_V = \frac{\text{standard deviation}}{\text{mean}} = \frac{\sigma}{\mu}$$

• It allows us to compare the variability across datasets on different scales.

Statistic	Sample 1	Sample 2
Raw data	[1, 10, 3, 50, 3, 7]	[1000, 1030, 1110, 900, 999]
Mean	12.33	1007.80
Standard deviation	17.10	67.37
Coefficient of variation	1.39	0.07

## Time-series analysis supported by Power Transformations

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#### ABSTRACT

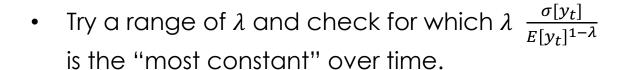
This paper presents some procedures aimed at helping an applied timeseries analyst in the use of power transformations. Two methods are proposed for selecting a variance-stabilizing transformation and another for bias-reduction of the forecast in the original scale. Since these methods are essentially model-independent, they can be employed with practically any type of time-series model. Some comparisons are made with other methods currently available and it is shown that those proposed here are either easier to apply or are more general, with a performance similar to or better than other competing procedures.

KEY WORDS ARIMA models Bias reduction Forecasting Taylor series approximation Time-series models Variance-stabilizing

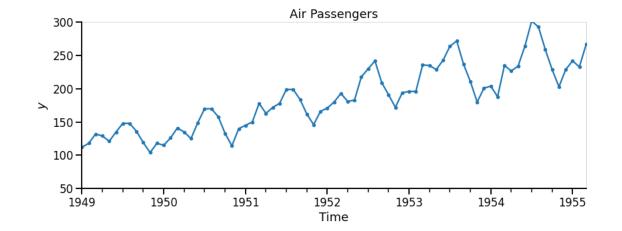
- We want to pick  $\lambda$  so that the variance of  $y_t^{(\lambda)}$  is constant.
- Guerrero [1] showed that this requirement implies that:

$$\frac{\sigma[y_t]}{E[y_t]^{1-\lambda}} = constant$$

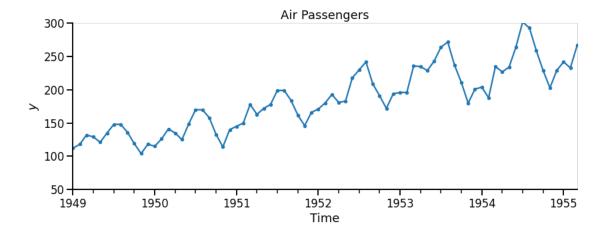
for all time steps t.



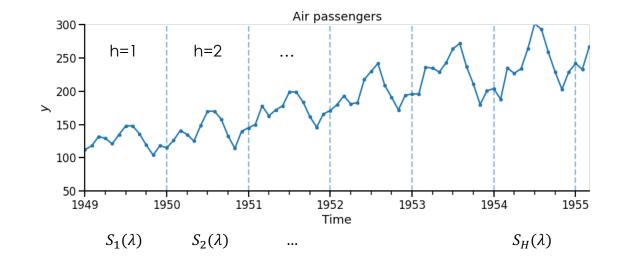
• In practice, we have one observation at each t. How do we calculate  $\sigma[y_t]$  and  $E[y_t]$ ?



• Split the time series into H evenly sized buckets (aka subseries), labelled by h.

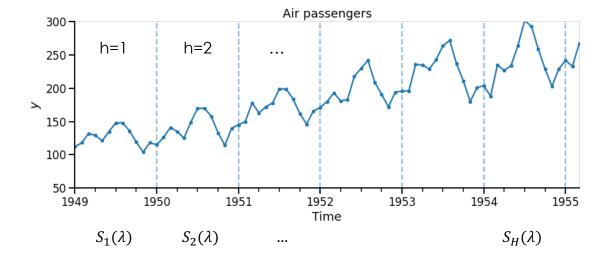


- Split the time series into H evenly sized buckets (aka subseries), labelled by h.
- Compute  $\sigma[y_t] \& E[y_t]$  within each subseries.
- Compute  $\frac{\sigma[y_t]}{E[y_t]^{1-\lambda}} = S_h(\lambda)$  for each subseries.
- How do we measure how constant  $S_h(\lambda)$  is across the time series? Use the coefficient of variation of  $S_h(\lambda)$  across all subseries,  $C_V(\lambda)$ !
- If  $C_V(\lambda)$  is low, it means that  $S_h(\lambda)$  is "more constant" across the time series.



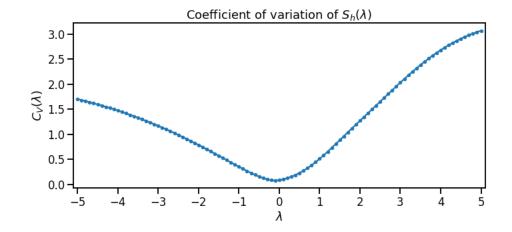
$$C_V(\lambda) = \frac{\sigma}{\mu} = \frac{\sigma[S_h(\lambda)]}{E[S_h(\lambda)]}$$

• Compute  $C_V(\lambda)$  at multiple values of  $\lambda$  between -5 and 5.



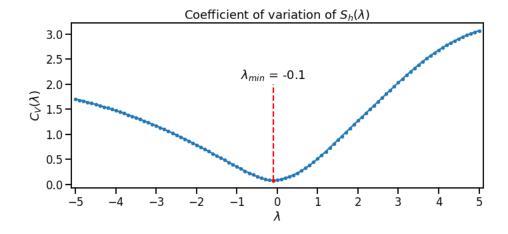
$$C_V(\lambda) = \frac{\sigma}{\mu} = \frac{\sigma[S_h(\lambda)]}{E[S_h(\lambda)]}$$

- Compute  $C_V(\lambda)$  at multiple values of  $\lambda$  between -5 and 5.
- Pick  $\lambda = \lambda_{min}$  which minimizes  $C_V(\lambda)$ .



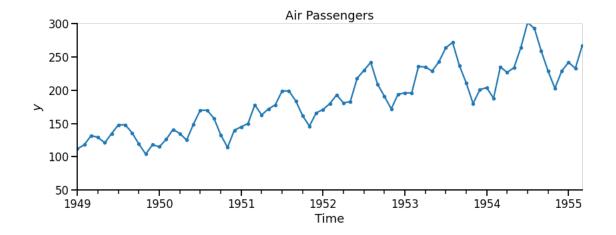
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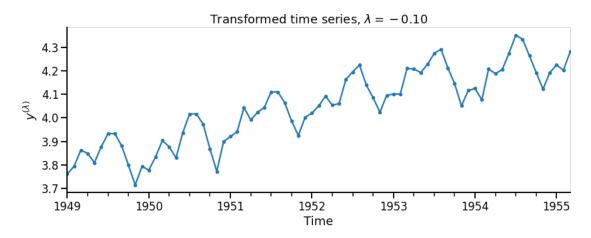
- Compute  $C_V(\lambda)$  at multiple values of  $\lambda$  between -5 and 5.
- Pick  $\lambda = \lambda_{min}$  which minimizes  $C_V(\lambda)$ .
- This value of  $\lambda$  creates a time series where  $\frac{\sigma[y_t]}{E[y_t]^{1-\lambda}}$  is the "most constant" across time.
- Which implies it's the best  $\lambda$  to use to cause the variance of  $y_t^{(\lambda)}$  to be constant.



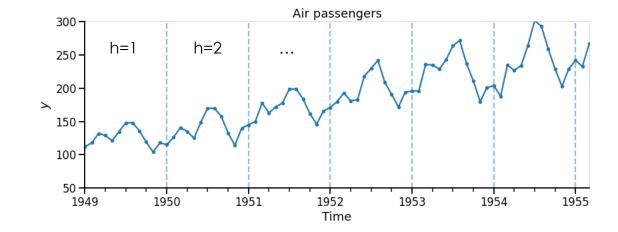
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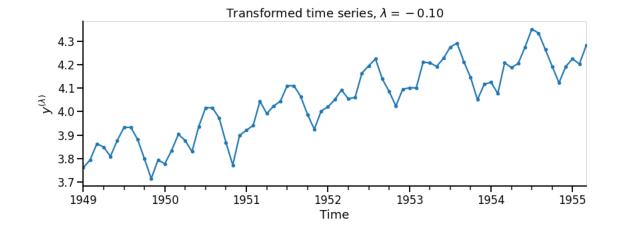


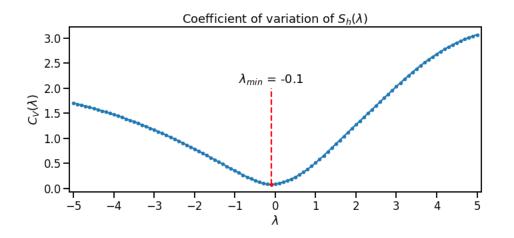
- Main parameter is the number of subseries,
   H, to split the original time series into.
- If the data has seasonality then split the subseries by the seasonal period (e.g., one subseries for each year if monthly data).
- If no seasonality, then split the timeseries into consecutive groups of size 2 to minimize loss of information caused by grouping.



# Why use the Guerrero method?

- Does not make any assumptions about the distribution of the data.
- Directly tries to stabilize the variance across the time series.
- Therefore, more relevant for our time series tasks (i.e., forecasting and decomposition).





# Box Cox implementation in sktime

#### BoxCoxTransformer

class BoxCoxTransformer(bounds=None, method='mle', sp=None)

[source]

Box-Cox power transform.

Box-Cox transformation is a power transformation that is used to make data more normally distributed and stabilize its variance based on the hyperparameter lambda. [1]

The BoxCoxTransformer solves for the lambda parameter used in the Box-Cox transformation given *method*, the optimization approach, and input data provided to *fit*. The use of Guerrero's method for solving for lambda requires the seasonal periodicity, *sp* be provided. [2]

Parameters: bounds : tuple

Lower and upper bounds used to restrict the feasible range when solving for the value of lambda.

method: {"pearsonr", "mle", "all", "guerrero"}, default="mle"

The optimization approach used to determine the lambda value used in the Box-Cox transformation.

sp : int

Seasonal periodicity of the data in integer form. Only used if method="guerrero" is chosen. Must be an integer >= 2.

from sktime.transformations.series.boxcox import BoxCoxTransformer
transformer = BoxCoxTransformer(method='querrero', sp=12)

```
transformer = BoxCoxTransformer(method='guerrero', sp=12)
data['y_g'] = transformer.fit_transform(data['y'])
transformer.lambda_
```

-0.10000000000001741

# Summary

Forecasting and decomposition methods sometimes work better if the variance is stable across the whole time series.

A Box Cox transform can stabilize the variance, but we need to pick a good value for the parameter  $\lambda$ .

Guerrero method selects  $\lambda$  that makes the variance of  $y^{(\lambda)}$  constant by minimizing the coefficient of variation.

# **Appendix: Guerrero method**

- We denote the Box Cox Transform of a variable Y as T(Y).
- We want the variance of the transformed variable to be constant:

$$Var[T(Y)] = c$$

• Taylor expand T(Y) about the mean of Y, E[Y], to first order:

$$T(Y) \approx T(E[Y]) + T'(E[Y])(E[Y] - Y) \text{ where } T'(Y) = \frac{\partial T}{\partial Y} = Y^{\lambda - 1}$$
 
$$\Rightarrow Var[T(Y)] \approx T'(E[Y])^2 Var[Y] = c$$

$$\Rightarrow \frac{Var[Y]^{\frac{1}{2}}}{E[Y]^{1-\lambda}} = \sqrt{c} = a$$