TIME SERIES 501

Lesson 1: Introduction to Time Series

Learning Objectives

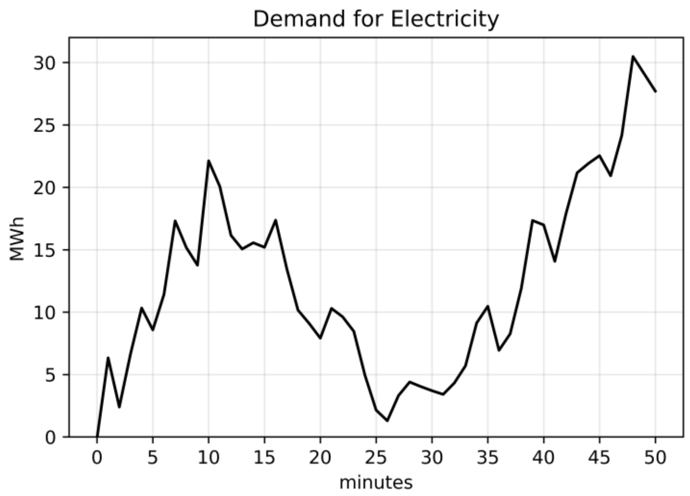
You will be able to do the following:

- Define "time series."
- Explain why time-series analysis is important.
- Identify time-series applications.
- Describe the components of time series.
- Describe and differentiate between additive, multiplicative, and pseudoadditive time-series models.
- Use Python* to decompose a time-series dataset.

What Is a Time Series?

A sequence of data points organized in time order.

- The sequence captures data at equally spaced points in time.
- Data collected irregularly is not considered a time series.



Time Series

Time-series data is common across many industries.

- Finance: stock prices, asset prices, macroeconomic factors
- E-Commerce: page views, new users, searches
- Business: transactions, revenue, inventory levels

Motivations for Using Time Series

Time-series methods are used to do the following:

- Understand the generative process underlying the observed data
- Fit a model in order to monitor or forecast a process

APPLICATIONS

Applications of Time Series

Time-series analysis is used in the following:

- Economic forecasting
- Stock-market analysis
- Demand planning and forecasting
- Anomaly detection
- And much more

Economic Forecasting

Macroeconomic predictions:

- World Trade Organization does time series forecasting to predict levels of international trade.
- Federal Reserve uses time-series forecasts of the economy to set interest rates.

Image source: https://commons.wikimedia.org/wiki/File:Ever_Given_container_ship.jpg
Source: https://www.econ-jobs.com/research/36056-Forecasting-international-trade-A-time-series-approach.pdf
Source: https://www.federalreserve.gov/pubs/feds/2009/200910/200910pap.pdf

Demand Forecasting

Used to predict demand, both overall and at more granular levels

- Amazon and other e-commerce companies use time-series modeling to predict demand at a product-geography level.

- Helps meet customer needs (fast shipping) and reduce inventory waste.

Image source: https://commons.wikimedia.org/wiki/File:Amazon_España_por_dentro_(20).jpg
Source: https://www.theverge.com/2014/1/18/5320636/amazon-plans-to-ship-your-packages-before-you-even-buy-them

Anomaly Detection

Particular kind of time-series analysis for detecting anomalies in time series

- Widely in manufacturing to detect defects and target preventive maintenance
- Now, with new IoT devices, techniques spreading to other machinery-heavy industries, such as petroleum and gas

Image source: https://en.wikipedia.org/wiki/Oil_platform#/media/File:Oil_platform_P-51_(Brazil).jpg
Source: https://arxiv.org/pdf/1607.02480.pdf
Petroleum source: www.mdpi.com/1424-8220/15/2/2774/pdf

TIME-SERIES COMPONENTS

Time-Series Components

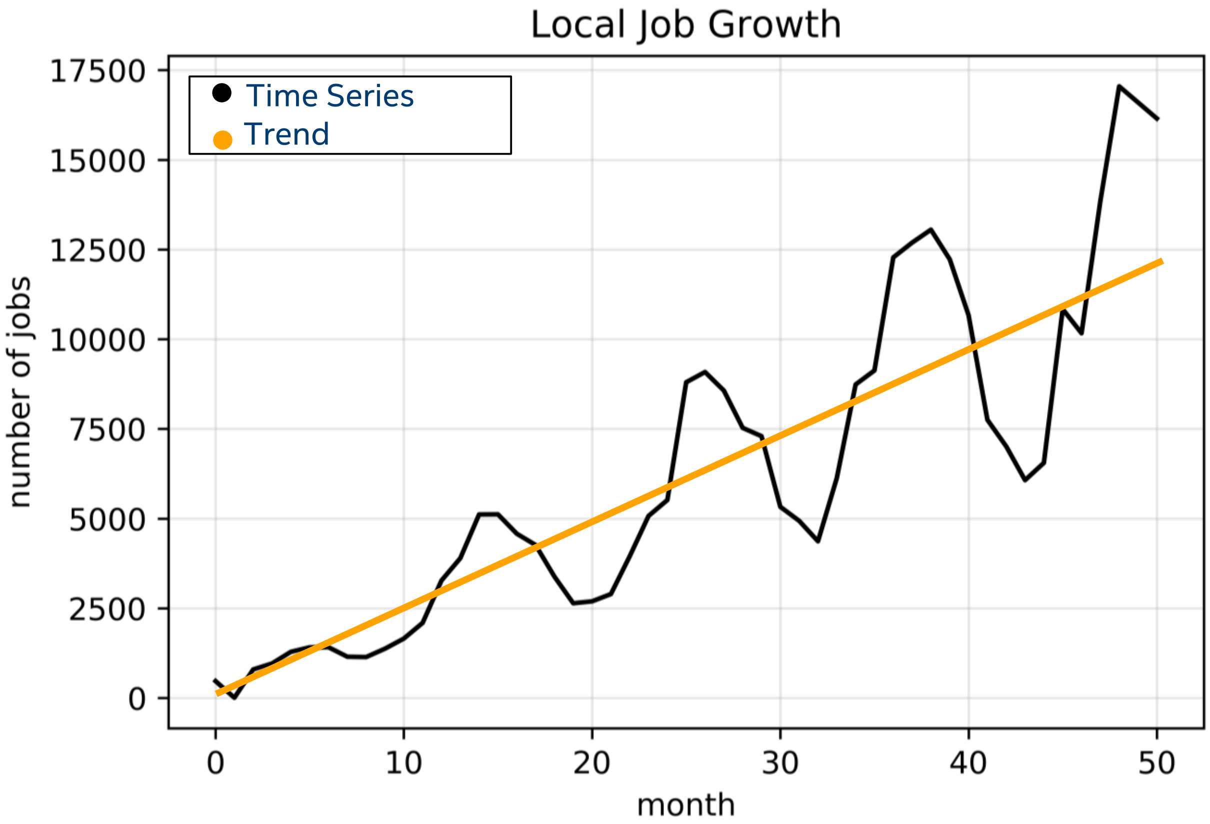
A time series has three components:

- **Trend** – long-term direction
- **Seasonality** – periodic behavior
- **Residual** – irregular fluctuations

Trend

Trend captures the general direction of the time series.

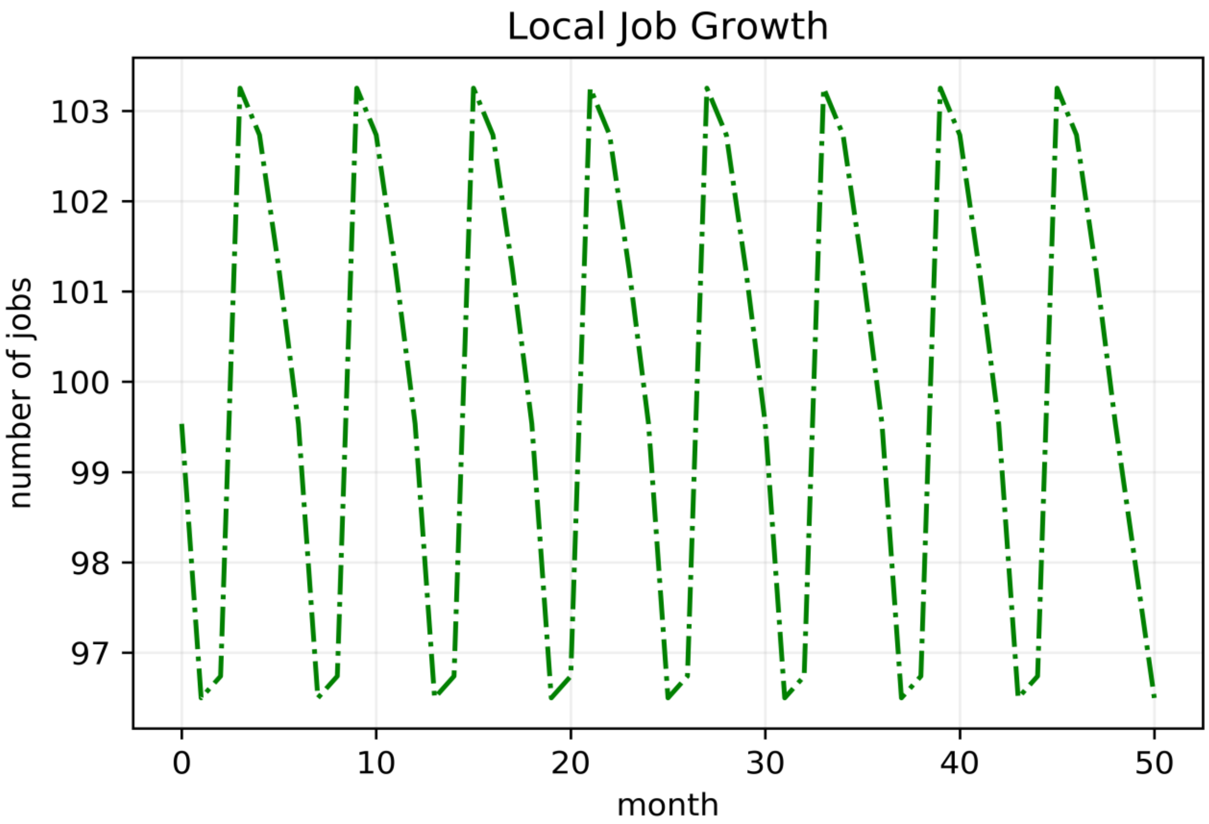
- For example, increasing job growth year over year despite seasonal fluctuations.
- Trend can be increasing, decreasing, or constant.
- It can increase or decrease in different ways (linearly, exponentially, or in other ways).


Local Job Growth
Time Series
Trend
17500
15000
12500
10000
7500
5000
2500
0
number of jobs
0
10
20
30
40
50
month

Seasonality

Seasonality captures effects that occur with specific frequency. It can be driven by many factors.

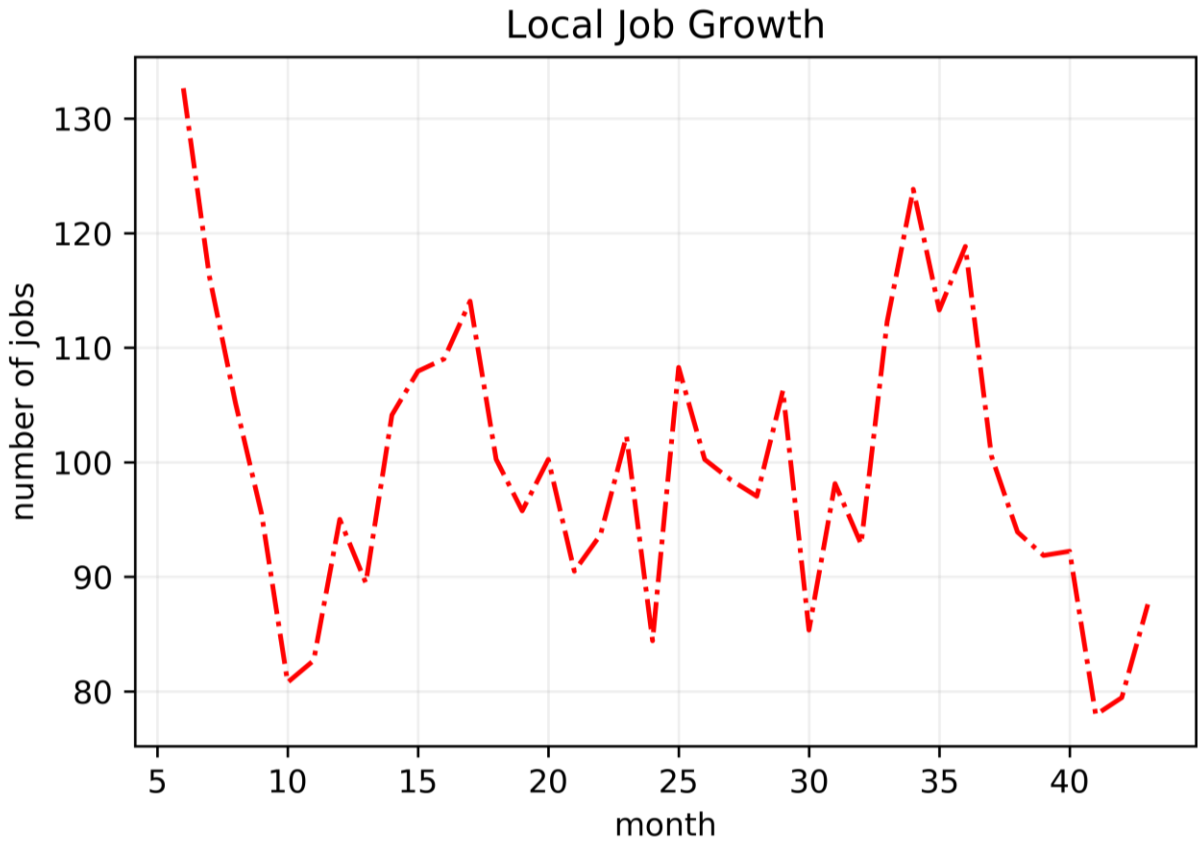
- Naturally occurring events, such as weather fluctuations caused by time of year
- Business or administrative procedures, such as start and end of a school year
- Social or cultural behavior, such as holidays or religious observances
- Fluctuations due to calendar events, such as the number of Mondays per month for trading or holidays that shift from year to year (Easter, Chinese New Year)


Local Job Growth
number of jobs
103
102
101
100
99
98
97
0
10
20
30
40
50
month

Residuals

Residuals are the random fluctuations left over after trend and seasonality are removed.

- They are what is left over after trend and seasonality are removed from the original time series.
  - You should not see a trend or seasonal pattern in the residual.
- They represent short-term fluctuations.
- They're either random or a portion of the trend or seasonality components was missed in the decomposition.


Local Job Growth
130
120
110
100
90
80
number of jobs
5
10
15
20
25
30
35
40
month

DECOMPOSITION MODELS

Decomposition Models

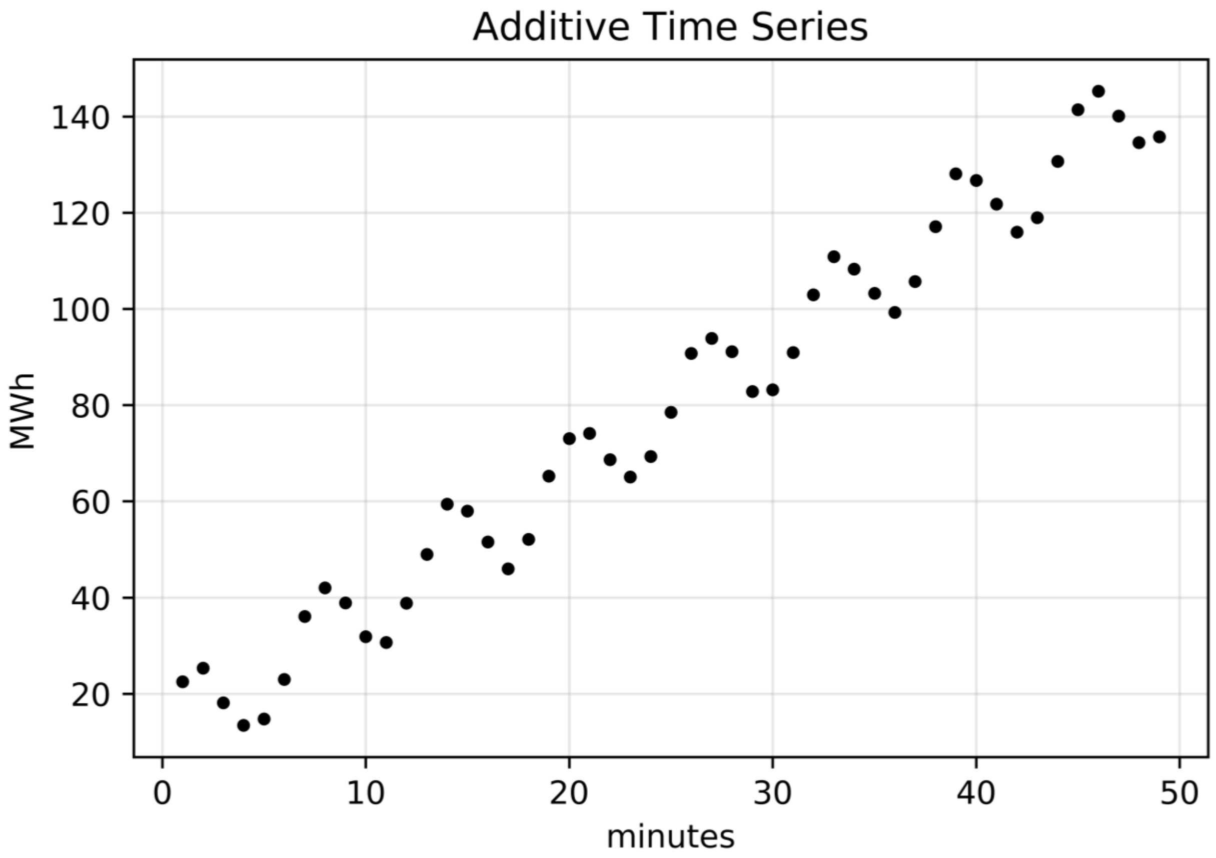
Time-series components can be decomposed with the following models:

- Additive decomposition
- Multiplicative decomposition
- Pseudoadditive decomposition

Additive Model

Additive models assume that the observed time series is the sum of its components.

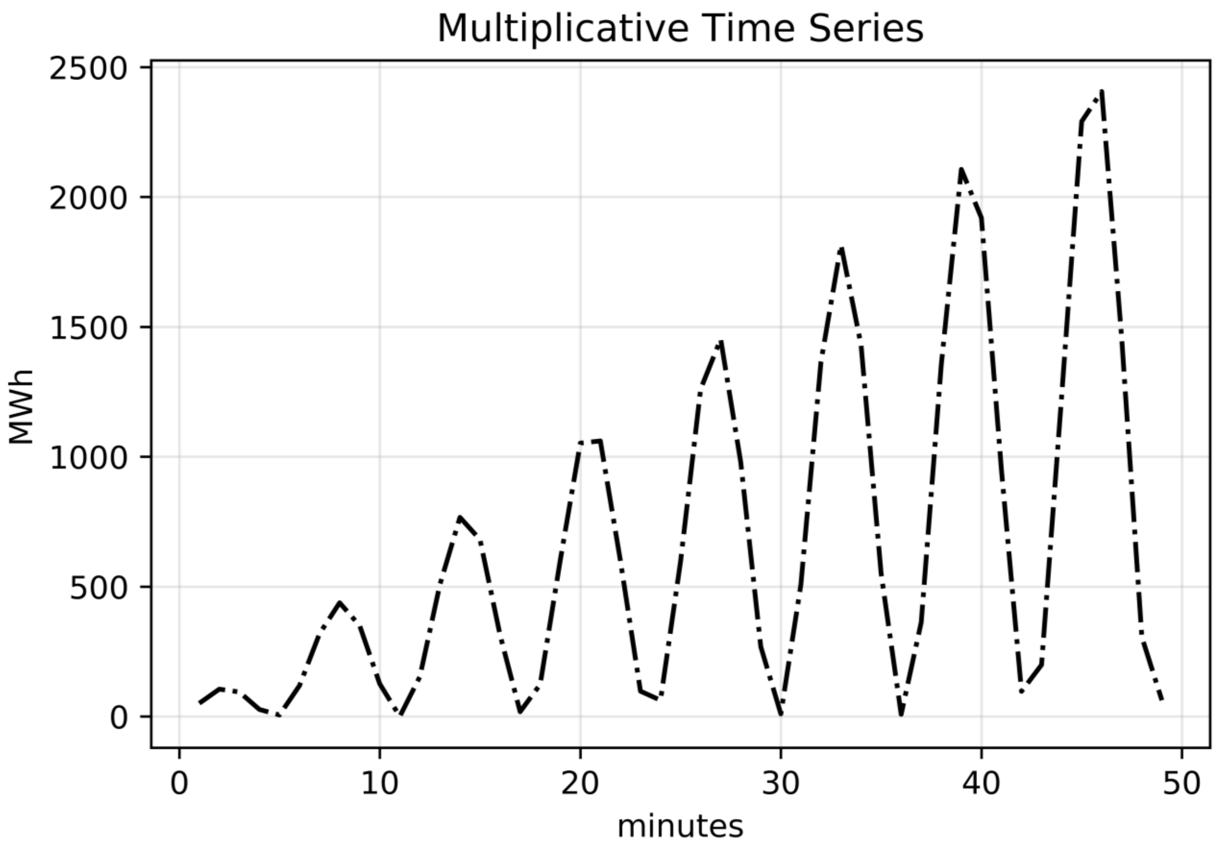
- **Observation = Trend + Seasonality + Residual**
- Additive models are used when the magnitudes of the seasonal and residual values are independent of trend.


Additive Time Series
MWh
minutes
20
40
60
80
100
120
140
0
10
20
30
40
50

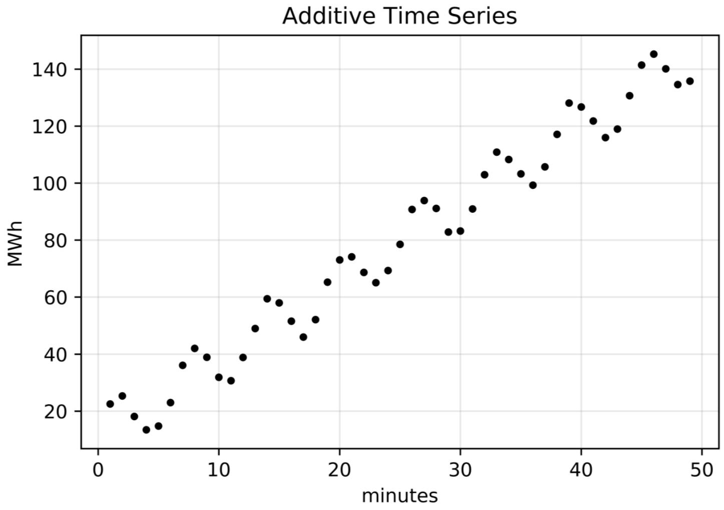
Multiplicative Model

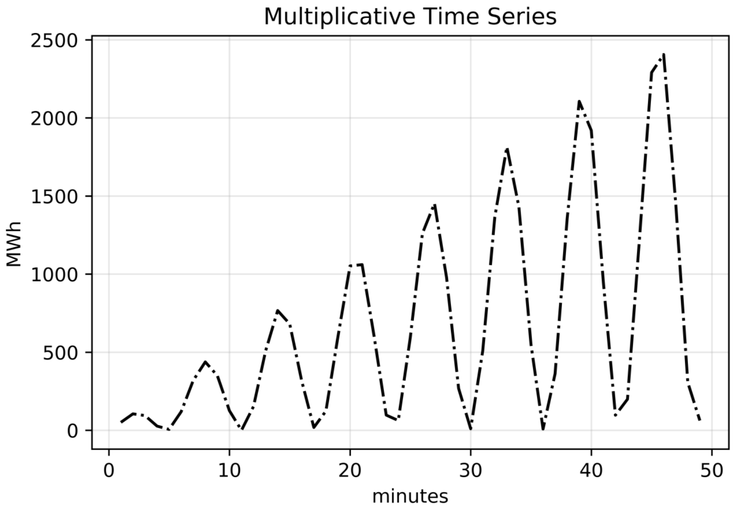
The observed time-series multiplicative models assume that the observed time series is the product of its components.

- **Observation = Trend * Seasonality * Residual**
- It is possible to transform a multiplicative model to an additive by applying a log transformation.
  - **log(Time*Seasonality*Residual) = log(Time) + log(Seasonality) + log(Residual)**
- Multiplicative models are used when the magnitudes of the seasonal and residual values fluctuate with trend.


Multiplicative Time Series
MWh
2500
2000
1500
1000
500
0
0
10
20
30
40
50
minutes

Additive vs. Multiplicative Models





The magnitudes of the seasonal and residual values fluctuate with trend.

The magnitudes of the seasonal and residual values are independent of trend.

Pseudoadditive Model

Pseudoadditive models combine elements of the additive and multiplicative models.

- Useful when time series values are close to or equal to zero and you require a multiplicative model.
- Division by zero becomes a problem in multiplicative models when this is the case.
- For example, rewriting the model as follows:
  - $O_t = T_t + T_t(S_t - 1) + T_t(R_t - 1) = T_t(S_t + R_t - 1)$

How to Decompose a Time Series

Of the many ways to decompose a time series, these are the most common:

- Single, double, or triple exponential smoothing
- Locally estimated scatterplot smoothing (LOESS)
- Frequency-based methods common in signal processing
- More on these methods in future lessons!

Using Python to Decompose Time Series

Next up is a look at applying these concepts in Python

- See notebook entitled *Introduction_to_Time_Series_student.ipynb*

Learning Objectives Recap

In this session you learned how to do the following:

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- Identify time series applications
- Describe the components of time series
- Describe and differentiate between additive, multiplicative, and pseudoadditive time series models
- Use Python to decompose a time-series dataset

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