Time Series

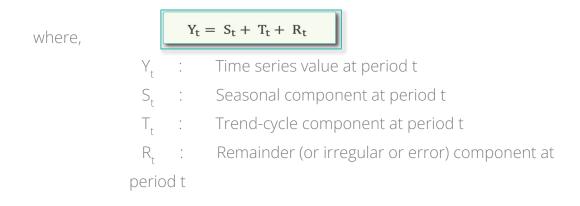
Decomposition

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Components of Time Series

- As we know, Trend and Seasonality are main components of Time Series.
- If we assume an additive model, we can write



• Alternatively, a multiplicative model would be written as





Understanding Moving Averages

- Moving Averages are averages calculated for consecutive data from overlapping subgroups of fixed length
- Moving averages smoothen a time series by filtering out random fluctuations

Day	End of Day Sales		Moving Average of Period 3	
1	1500	\longrightarrow	NA	
2	2100		NA	The first 2 MA
3	1750		(1500+2100+1750)/3=1783.33	values for lengt
4	1900		(1300+2100+1730)/3-1763.33	3 are not calculated
5	1650		(2100+1750+1900)/3=1916.67	Calculated
			(1750+1000+1650)/2-1766-67	
			(1750+1900+1650)/3=1766.67	

- Period of the moving average depends on type of data
- Non-seasonal data: Shorter length (Typically 3 period or 5 period MA is considered)
- Seasonal data: Typical period is 12 for monthly data and 4 for quarterly data

Decomposition is a statistical method that deconstructs a time series.

Steps to follow:

Find Trend

Obtain moving averages covering one season – This provides trend component of the time series

Eliminate Trend

Eliminate trend component from original time series. Calculate \mathbf{Y}_{t} – \mathbf{T}_{t}

Estimate Seasonality To estimate the seasonal component for a given time period, simply average the de-trended values for that time period. These seasonal indexes are then adjusted to ensure that they add to zero

The remainder component is calculated by subtracting the estimated seasonal and trend-cycle components

Suppose we have monthly time series data, for three years 2014, 2015 and 2016:





(Consider moving average period of 13 - previous 6 months, next 6 months and current month to calculate moving average of current month)

This gives the trend component T_t

Step 2 ☐ Eliminating Trend

Remove T_t from the original time series Y_t

Step 3 ☐ Estimate Seasonal Component

The seasonal index for July is the average of all the de-trended July values in the data i.e. Average of De-trended July 2014, July 2015 and July 2016

Case Study

Background

Monthly Sales Data for 3 Years (2013, 2014, 2015)

Objective

• To decompose time series into its components and study each component separately.

Available Information

- Sample size is 36
- · Variables: Year, Month, Sales

Data Snapshot

Sales Data for 3 Years

Variables

Year	Month	Sales
2013	Jan	123
2013	Feb	142
2013	Mar	164
2013	Apr	173
2013	May	183
2013	Jun	192
2013	Jul	199
2013	Aug	203
2013	Sep	207
2013	Oct	209
2013	Nov	214
2013	Dec	255
2014	Jan	223
2222	5 <u>2</u> 6	200209

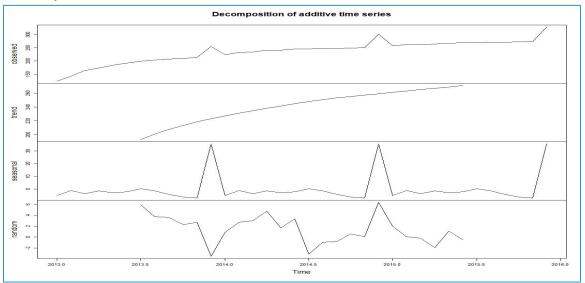
Monthly Observations

Columns	Description	Type	Measurement	Possible values
Year	Year	Numeric	2013, 2014, 2015	3
Month	Month	Character	Jan - Dec	12
Sales	Sales in USD Million	numeric	USD Million	Positive values

Time Series Decomposition

```
salesdata<-read.csv("Sales Data for 3 Years.csv",header=TRUE)</pre>
salesseries<-ts(salesdata$Sales,start=c(2013,1), end=c(2015,12),</pre>
frequency=12)
                    ts() converts a column from a data frame to a
                     simple time series object.
                    start= and end= arguments specify the x-axis
                     scale. (Year and month in this case).
                    frequency=12 tells that we have monthly data
                                      decompose() performs classical seasonal
decomp<-decompose(salesseries) ←</pre>
plot(decomp)
                                      decomposition through moving averages.
                                      plot() of decompose object gives a 4-level
                                      visual representation.
```

Output



Interpretation:

- ☐ Trend not calculated for first/last few values
- Seasonal Component repeats from year to year



#Analysing the decompose() object. Each component can be separately viewed by using the \$ operator

decomp\$seasonal

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	0ct
2013	COST SUSPENSION STREET	CHARLES BERTHARD BOOK STORE	The second secon	SO THE PART OF THE	GEORGE STATE OF THE STATE OF TH	-2.2319444			NO NEW YORK AND ADDRESS.	
						-2.2319444				
7 Y 3 TO 1 3						-2.2319444				
2013			-3./301111	-1.3001944	-2.6319444	-2.2319444	0.234/222	-1.3230944	-4.0944444	-0.44032/6
2012	Nov	Dec								
	-7.1277778									
70.00	-7.1277778									
2015	-7.1277778	35.5368056								

decomp\$trend

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	0ct	No∨	Dec
2013	NA	NA	NA	NA	NA	NA	192.8333	200.7708	207.4500	213.1958	218.4083	223.0167
2014	227.1667	230.9625	234.5500	237.9292	241.1000	244.5167	247.8917	250.5750	252.9333	254.9917	257.0417	259.1042
2015	261.0417	262.9958	264.9167	266.8417	268.7583	270.8417	NA	NA	NA	NA	NA	NA

decomp\$random

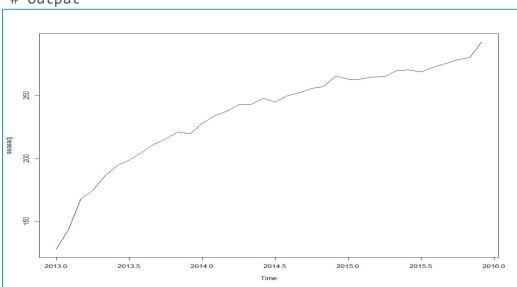
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
2013	NA	NA	NA	NA	NA	NA	5.93194444	3.75486111	3.6444444
2014	0.84027778	2.71944444	2.98611111	4.75902778	1.73194444	3.31527778	-3.12638889	-0.94930556	-0.83888889
2015	1.96527778	0.08611111	-0.18055556	-1.95347222	1.07361111	-0.50972222	NA	NA	NA
1111	0ct	Nov	Dec						11.11
2013	2.25069444	2.71944444	-3.55347222						
2014	0.55486111	0.08611111	6.35902778						
2015	NA	NA	NA						

Why are NAs getting generated?

Doing Seasonal Adjustment

```
seasadj <- salesseries - decomp$seasonal
plot(seasadj)</pre>
```

Output



Interpretation:

☐ This plot shows seasonally adjusted time series

Time Series Decomposition – Local Regression Method (LOESS)

Loess is the short form of Local Regression method

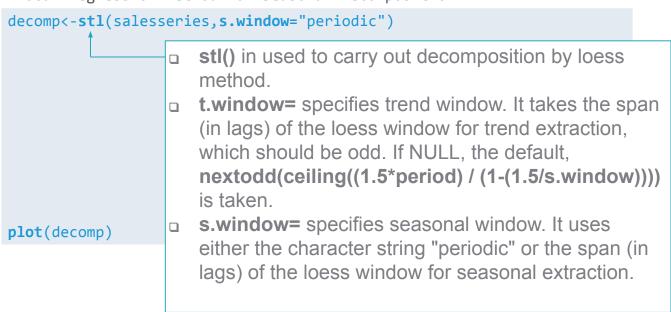
- Time series decomposition by Loess method not only seasonally adjusts a series but it also helps in modeling the series and understanding all the components of variability in the series.
- It is a non parametric generalisation of ordinary least squares regression.
- The fitting technique does not require a priori specification of the relationship between the dependent and independent variables.

STL is an acronym for "Seasonal and Trend Decomposition using Loess"

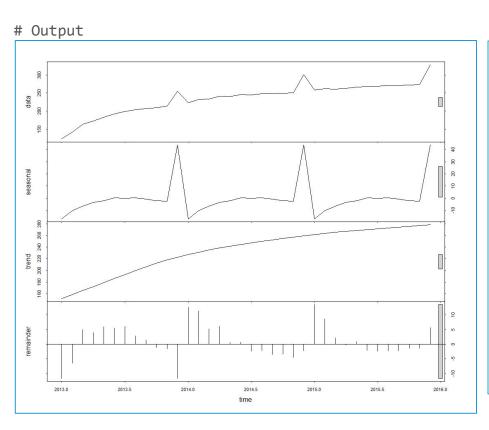
STL works by iterating through smoothing of the seasonal and trend components.
 STL is a procedure for regular time series, so the design points of the smoothing operation are equally-spaced.

Time Series Decomposition – Local Regression Method (LOESS)

#Local Regression Method for Seasonal Decomposition



Time Series Decomposition – Local Regression Method (LOESS)



Interpretation

- The data shows trend and seasonality.
- Note that trend values are estimated for all periods (unlike decompose function)

Quick Recap

What is Decomposition

- A time series is made up of multiple components such as seasonality, trend, randomness.
- Sometimes, studying these components separately provides a more comprehensive insight about the series.

LOESS Method

 Loess is a method for estimating nonlinear relationships while STL is an acronym for Seasonal and Trend decomposition using Loess.

Decomposition in R

- **decompose()** carries out simple seasonal decomposition
- **stl()** is used for doing decomposition by LOESS method