# Road map!

- Module 1- Introduction to Deep Forecasting
- Module 2- Setting up Deep Forecasting Environment
- Module 3- Exponential Smoothing
- Module 4- ARIMA models
- Module 5- Machine Learning for Time series Forecasting
- Module 6- Deep Neural Networks
- Module 7- Deep Sequence Modeling (RNN, LSTM)
- Module 8- Transformers (Attention is all you need!)
- Module 9- Prophet and Neural Prophet

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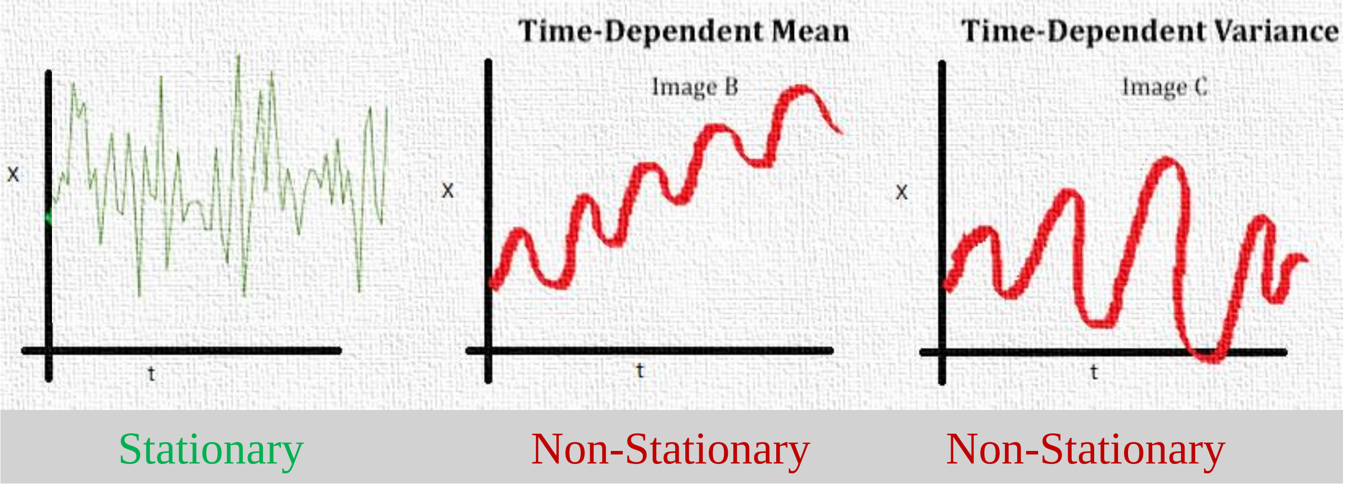
# Module 4 – Part I
# ARIMA models' Prerequisites
# ACF, PACF, Stationarity, Differencing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# ARIMA models prerequisites

- ARIMA stands for AutoRegressive Integrated Moving Average. It is a class of statistical models for analyzing and forecasting time series data.
- ETS and ARIMA models are two popular models for forecasting time series data. They offer complementary approaches to addressing the challenges of time series forecasting.
- ARIMA models describe autocorrelations in the data, whereas ETS models describe trends and seasonality.
- Let's review some prerequisites before moving forward with the models:

ACF → PACF → Stationarity → Differencing

# Autocorrelation

- Autocorrelation, also known as serial correlation, is a measure of the correlation between a time series and a lagged version of itself.
- It is used to assess the degree to which the past values of a time series are predictive of its future values.

$$r_k = \frac{\sum_{t=k+1}^{T} (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T} (y_t - \bar{y})^2}$$

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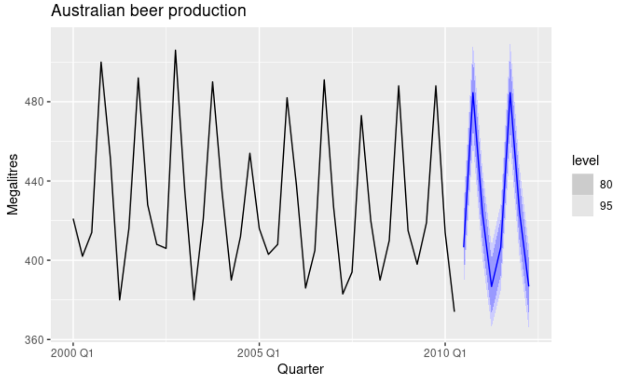
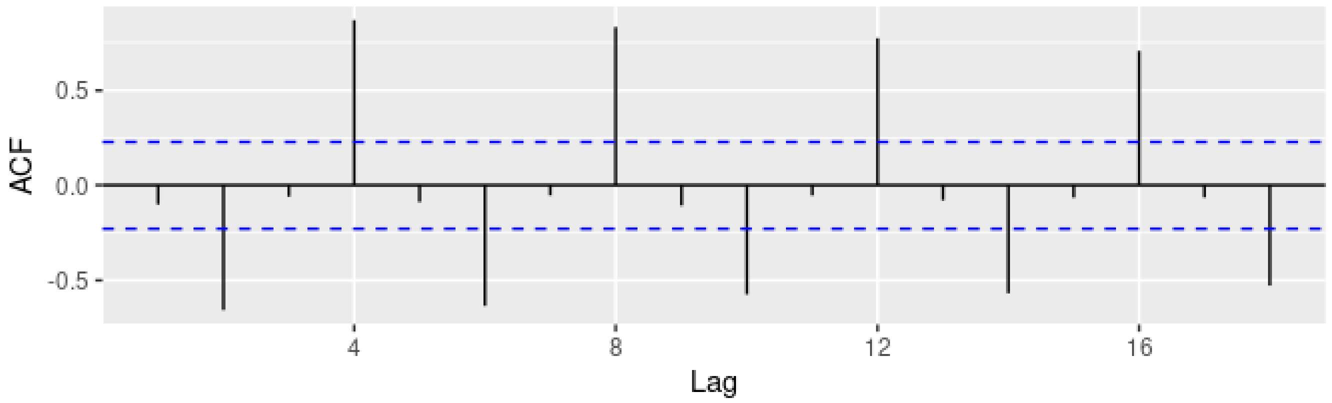
# ACF: Autocorrelation Function

- The autocorrelation function (ACF) is a statistical tool that can be used to measure the autocorrelation of a time series.
- It calculates the correlation between the time series and lagged versions of itself at different lag periods.



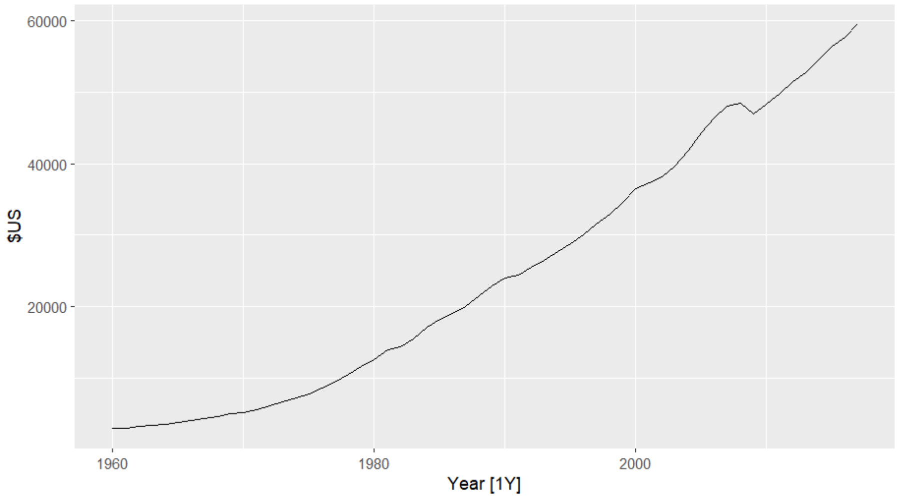

| $r_1$ | $r_2$ | $r_3$ | $r_4$ | $r_5$ | $r_6$ | $r_7$ | $r_8$ | $r_9$ |
|---|---|---|---|---|---|---|---|---|
| -0.102 | -0.657 | -0.060 | 0.869 | -0.089 | -0.635 | -0.054 | 0.832 | -0.108 |



# Partial Autocorrelation

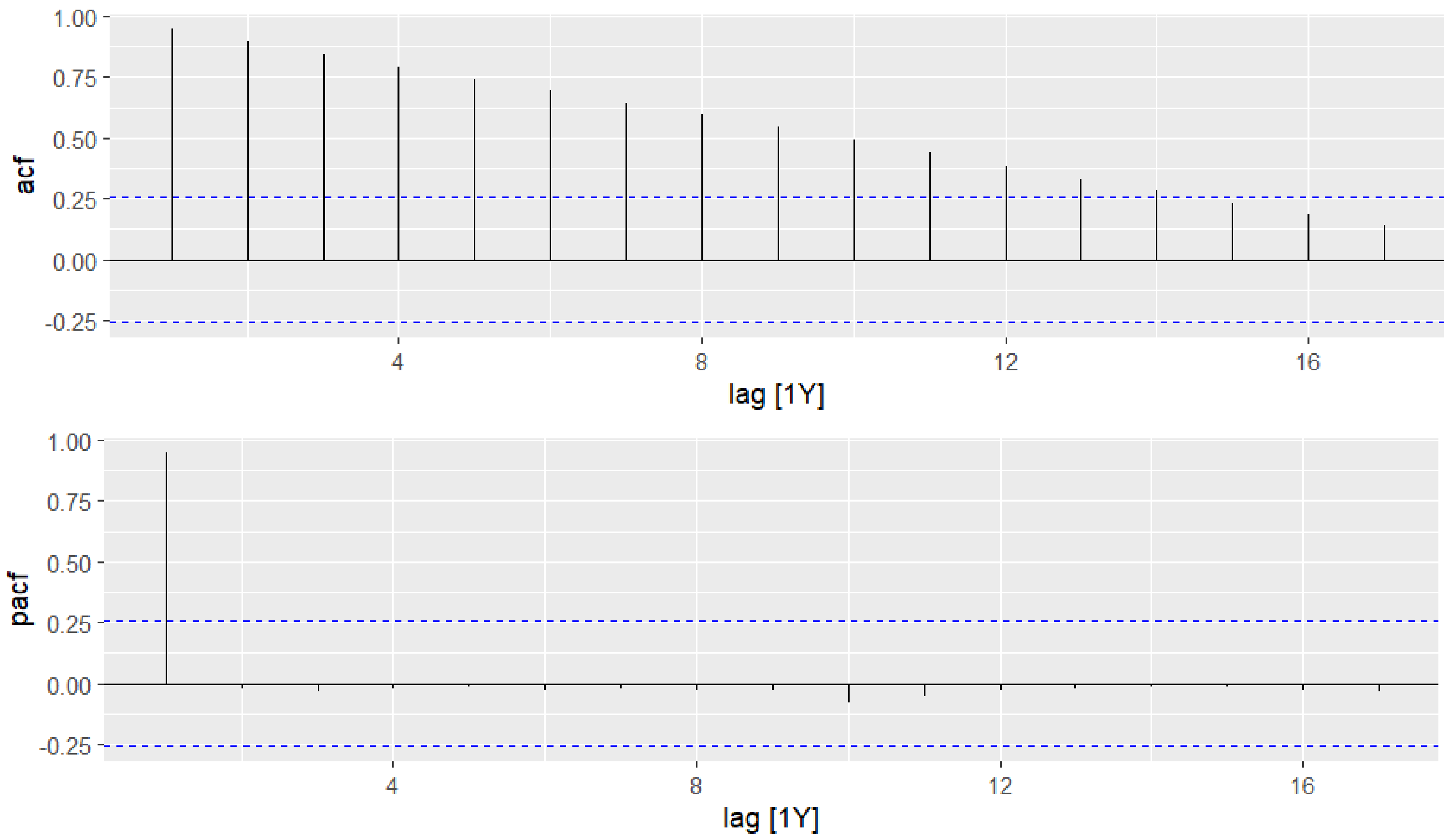
- Partial autocorrelation, also known as partial serial correlation, is a measure of the correlation between a time series and a lagged version of itself, controlling for the effects of intermediate lag periods.
- $y_t$ and $y_{t-2}$ might be correlated, simply because they are both connected to $y_{t-1}$, rather than because of any new information contained in $y_{t-2}$. Partial autocorrelation overcomes this problem.

US Annual GDP per capita (1960-2017)



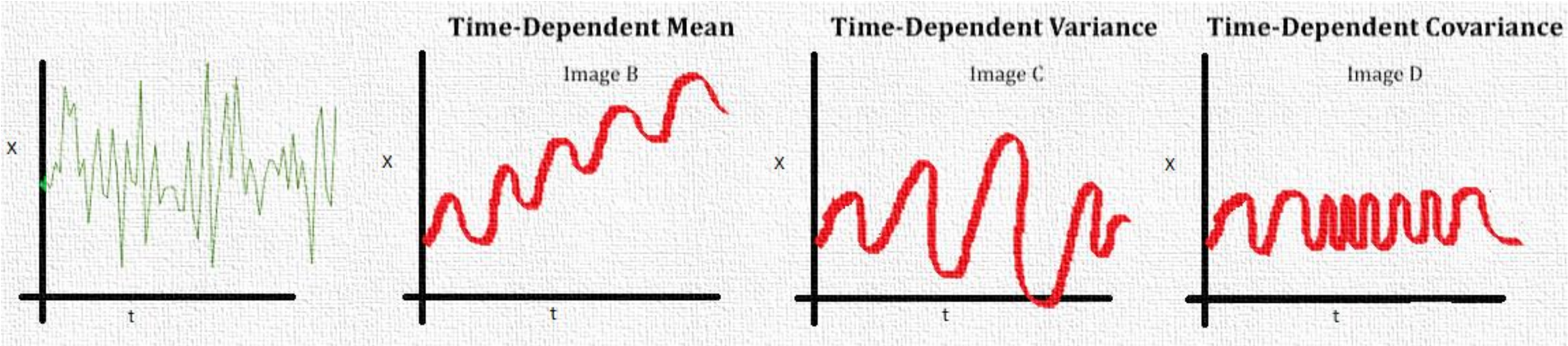
# PACF: Partial Autocorrelation Function

- PACF is a statistical tool that can be used to measure the partial autocorrelation of a time series.



# Stationarity

- Stationary vs Non-Stationary Data. What makes a data set Stationary?
- In a stationary timeseries, the statistical properties do not depend on the time

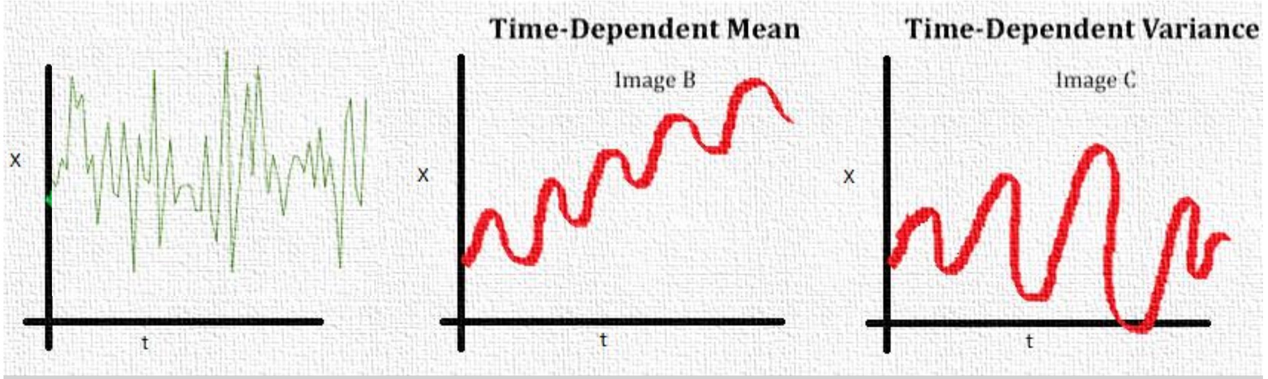



| Stationary | Non-Stationary | Non-Stationary | Non-Stationary |
| --- | --- | --- | --- |

- Data with trend and seasonality are NOT stationary!

# Weak vs Strong Stationarity

- Strong stationarity: mean, variance and autocovariance are constant over time
- Weak stationarity: mean and variance are constant overtime
- ARIMA models require weak stationarity if the autocovariance is not changing too rapidly over time.




Stationary Non-Stationary Non-Stationary

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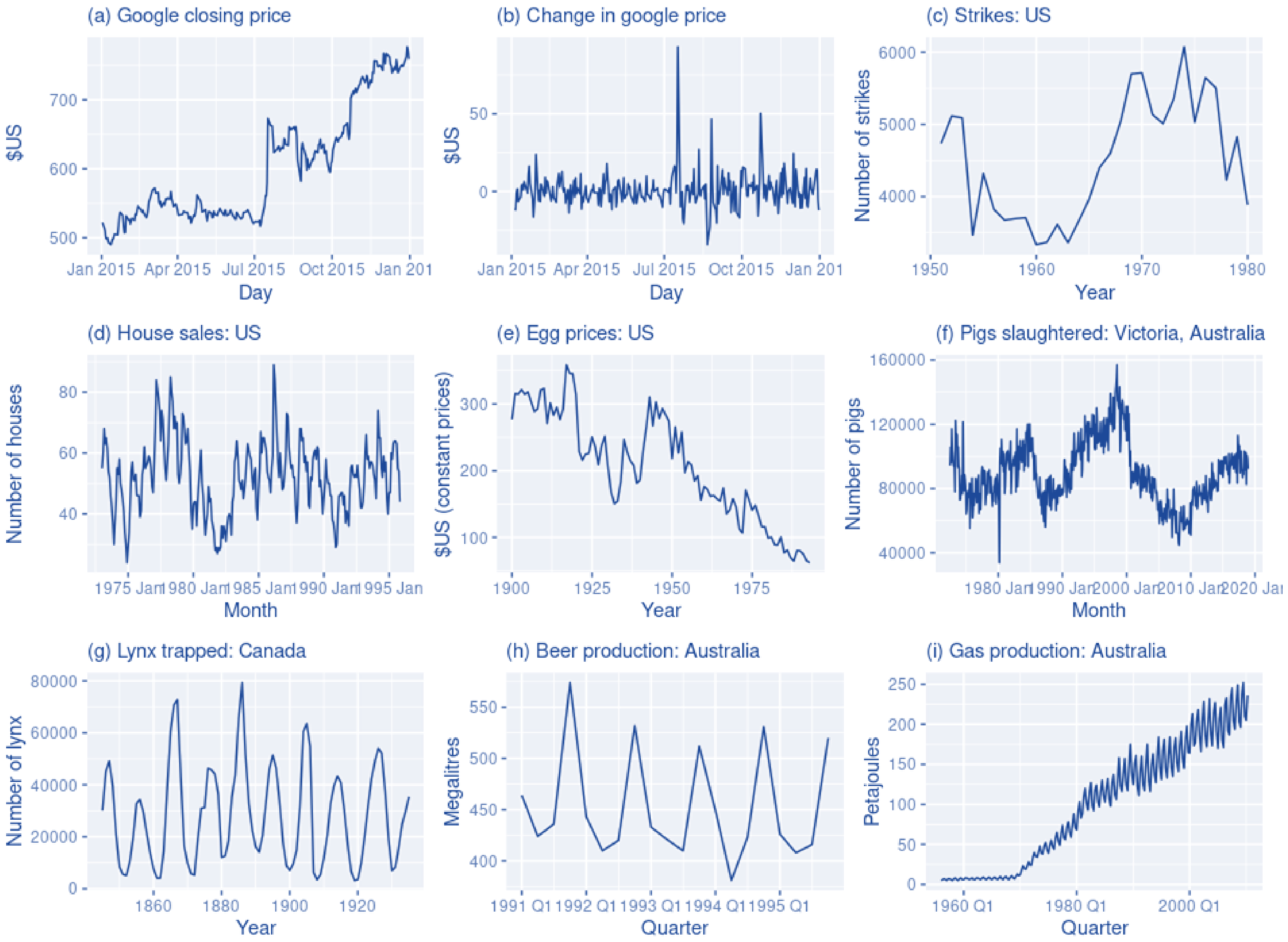
# Which ones are stationary?



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# Differencing

- Differencing: Computing the difference between consecutive observations.
- Differencing helps to stabilize the mean of a time series by removing changes in the level and therefore reducing the trend and seasonality.
- Recall: Transformations help to stabilize the variance of a time series.

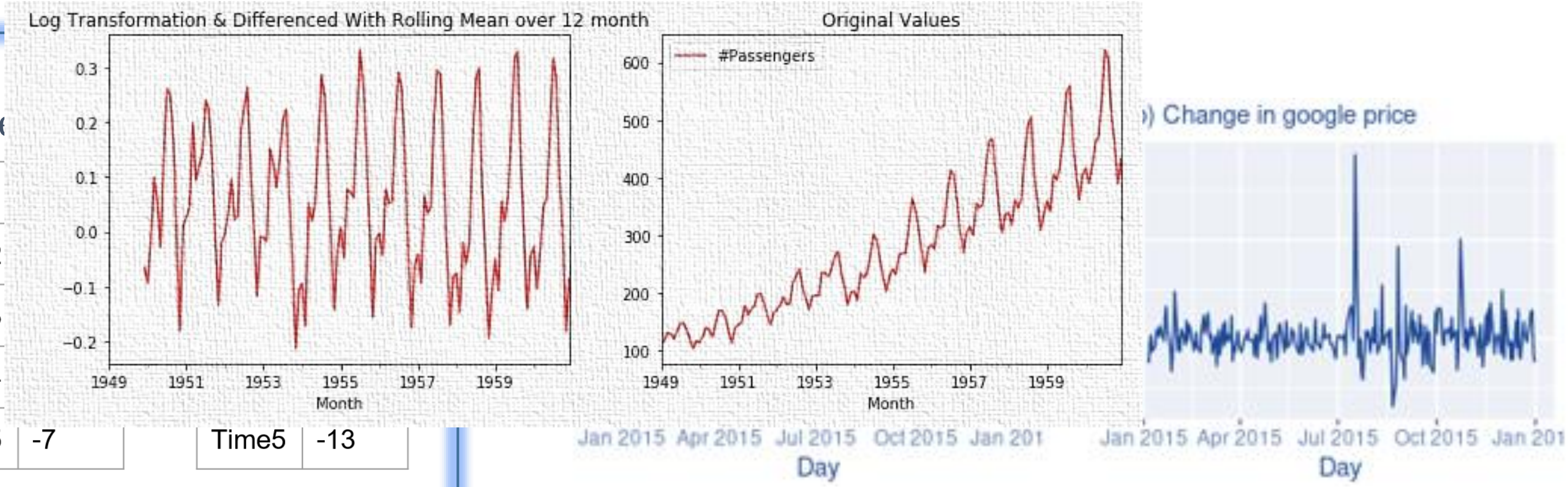
Original data

| | |
|---|---|
| Time1 | 10 |
| Time2 | 12 |
| Time3 | 8 |
| Time4 | 14 |
| Time5 | 7 |

1st diffe

| | |
|---|---|
| Time1 | |
| Time2 | |
| Time3 | |
| Time4 | |
| Time5 | -7 |

| | |
|---|---|
| Time5 | -13 |

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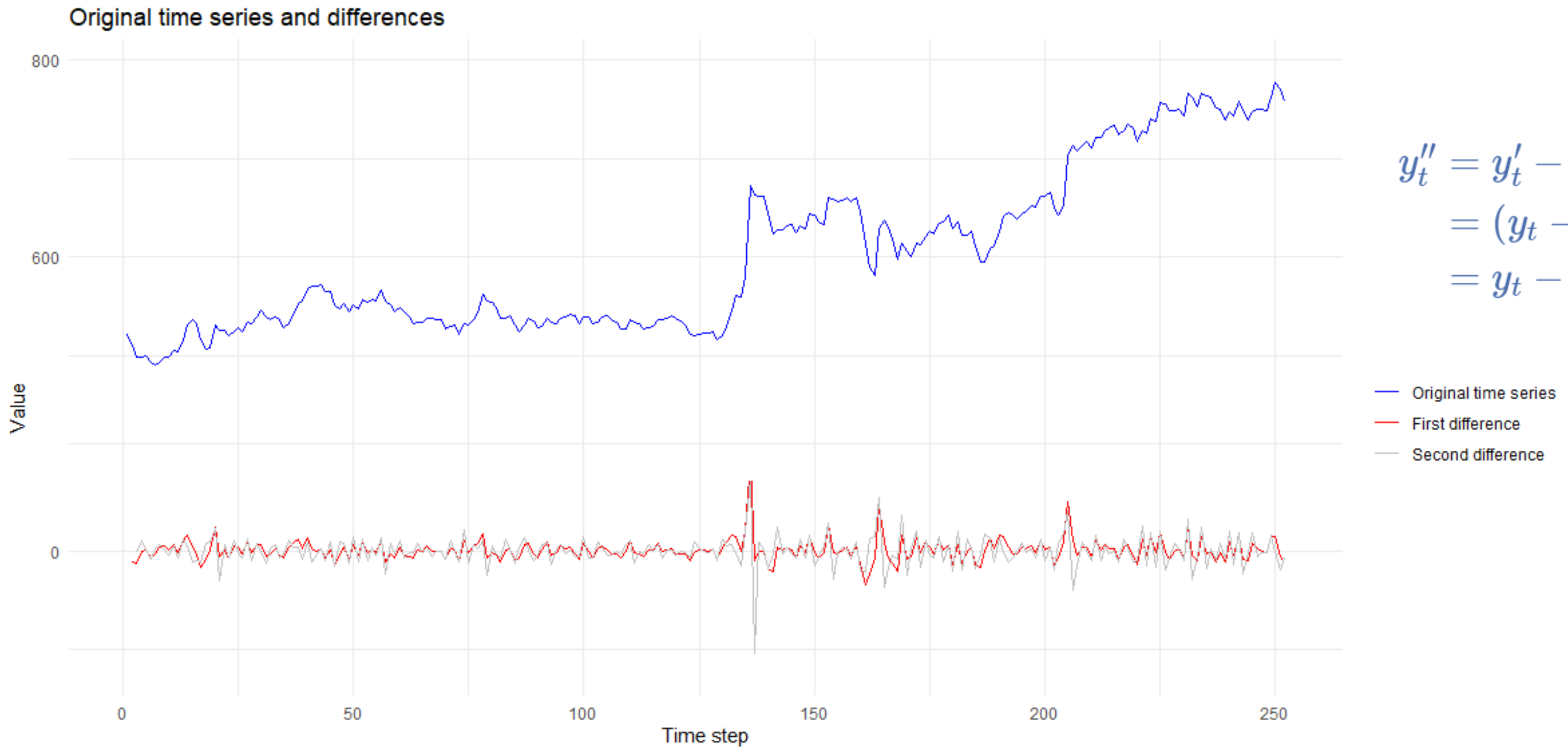
# 2nd Differencing

- Occasionally the differenced data will not appear to be stationary, and it may be necessary to difference the data a second time to obtain a stationary series.
- Second differencing is change in change.
- In practice, it is almost never necessary to go beyond second-order differences.




$$
\begin{aligned}
y''_t &= y'_t - y'_{t-1} \\
&= (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \\
&= y_t - 2y_{t-1} + y_{t-2}.
\end{aligned}
$$

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# Seasonal Differencing

- A seasonal difference is the difference between an observation and the previous observation from the same season.

$$y'_t = y_t - y_{t-m}$$

- m is the number of seasons. This is also called lag-m difference.
- If seasonal differenced is white noise, then

$$y_t = y_{t-m} + \varepsilon_t$$

- Recall:
  - Seasonal Naïve forecast: each forecast set to be equal to the last observed value from the same season

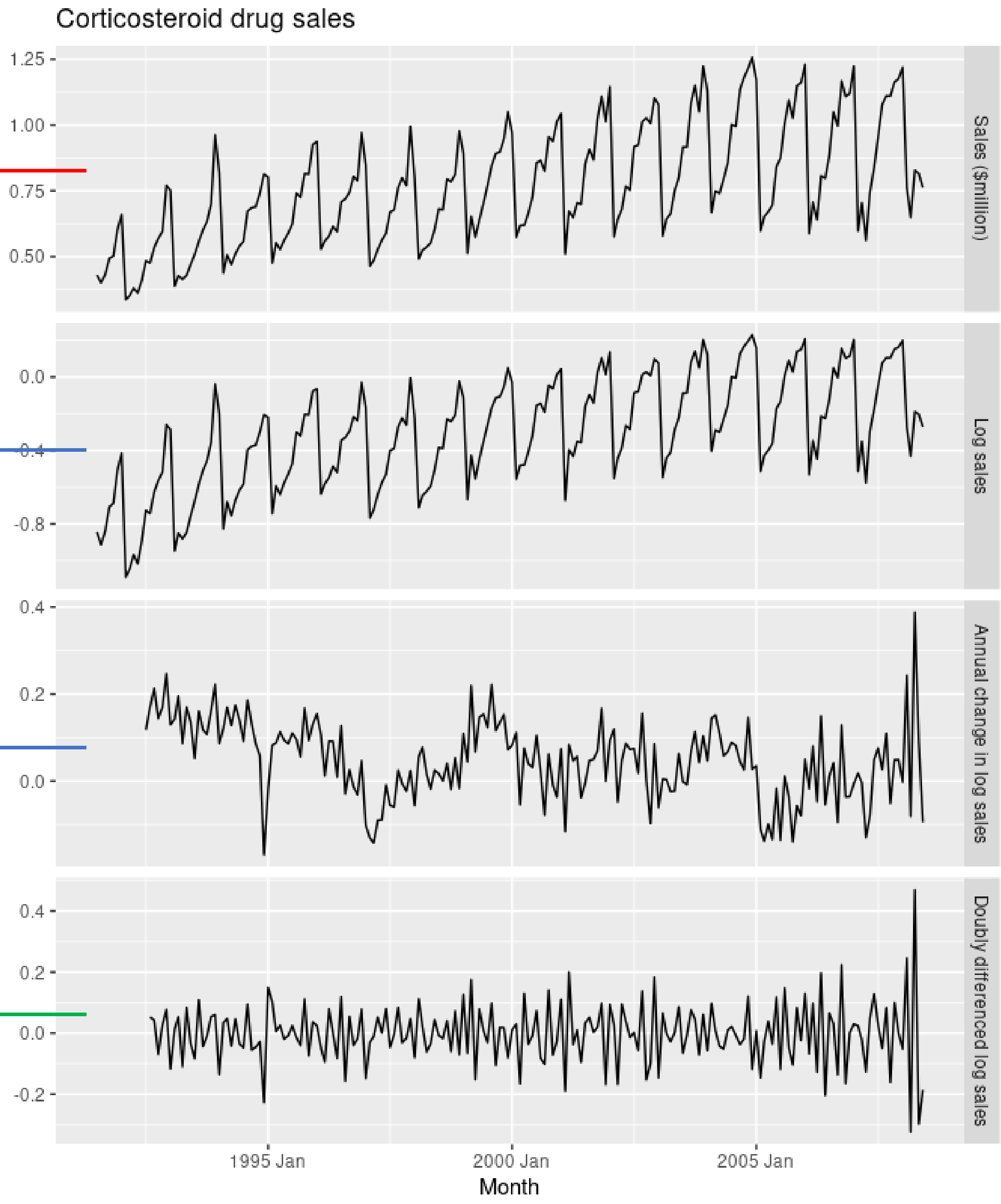
# Put it together!

Original data

Log transformed

Seasonal difference

1st differenced seasonal difference

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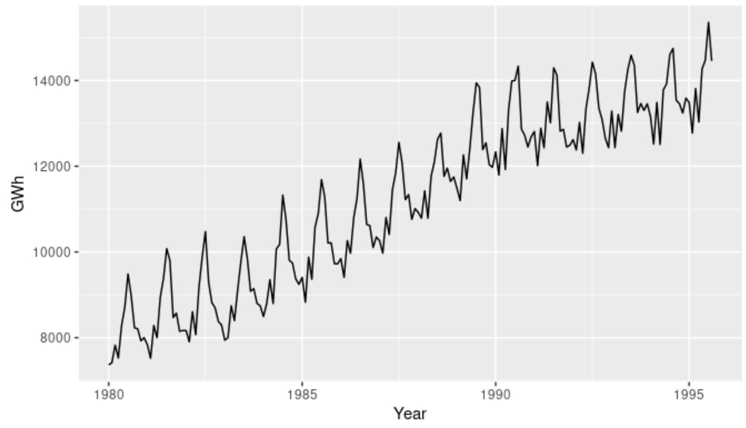
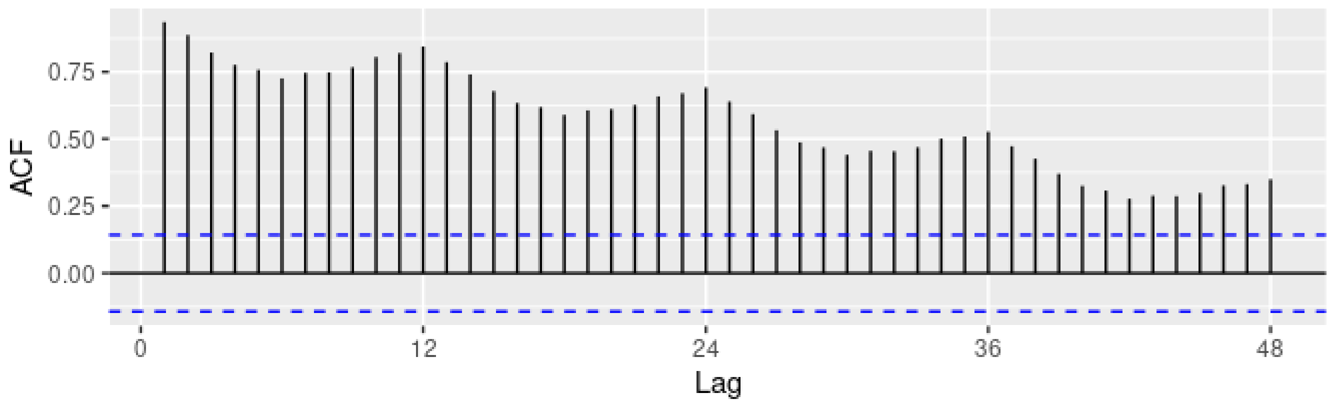
# Recall: Trend and seasonality in ACF plots

- Autocorrelation can be useful for identifying patterns and trends in time series data.
- The ACF of trended time series tend to have positive values that slowly decrease as the lags increase.
- Fore seasonal data, the autocorrelations are larger for the seasonal lags than for other lags.

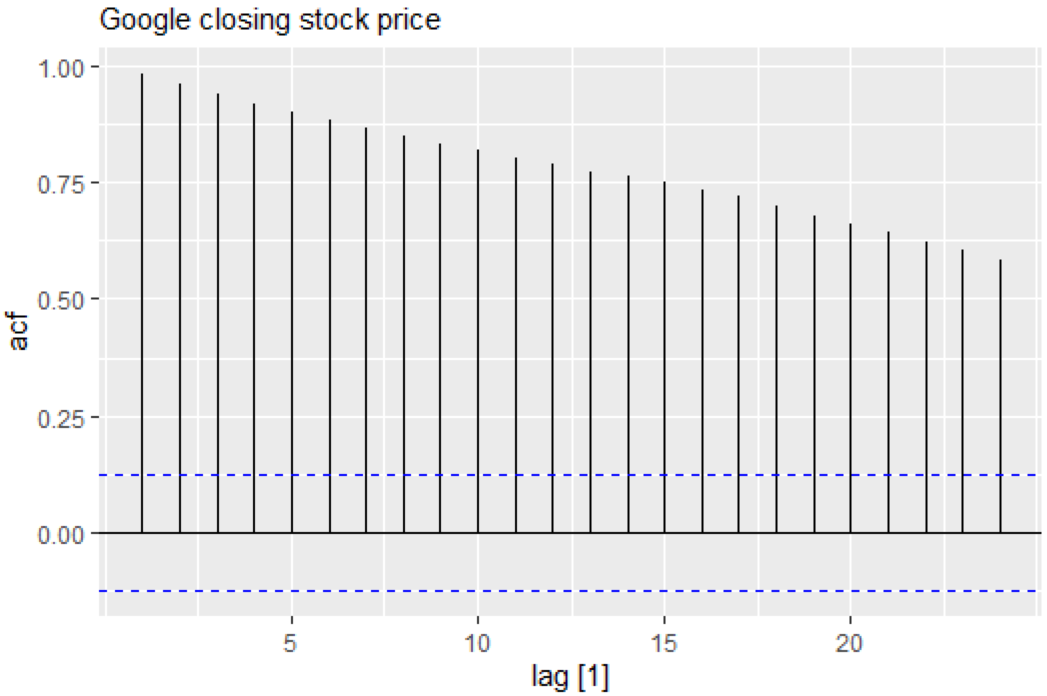
Monthly Electricity Demand



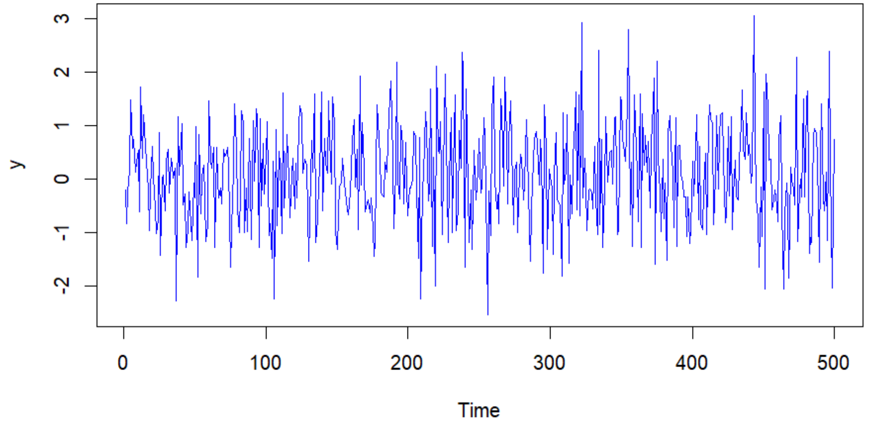
# ACF plots and Stationarity

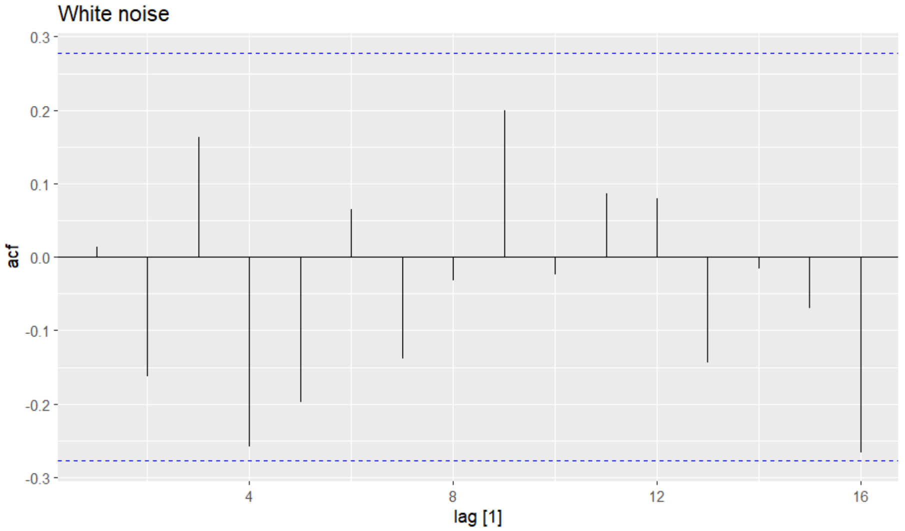
- For stationary data,
  - The ACF plot drops to zero quickly.
  - $r_1$ is mostly large and positive.

# White Noise

- White noise can be thought of as a random sequence of iid values (independent and identically distributed) characterized by a distribution.
- White noise has **zero mean** and **finite variance.** $\epsilon_t \sim D(0, \sigma^2)$
- White noise data show no autocorrelation.

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# Random Walk

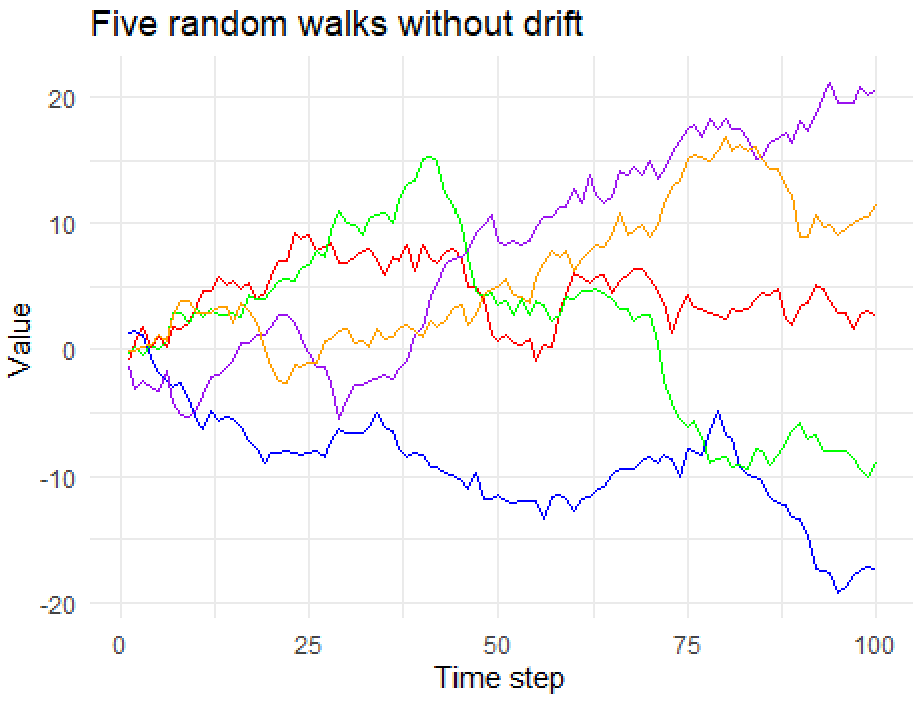
- Random Walk: When the 1st differenced series is white noise

$$y_t - y_{t-1} = \varepsilon_t \longrightarrow \boxed{y_t = y_{t-1} + \varepsilon_t}$$

- Random walk models are widely used for non-stationary data, particularly financial and economic data.

- Random walks typically have long periods of up or down trend + sudden change in direction.

- Random walk with no drift = Naïve forecasting model

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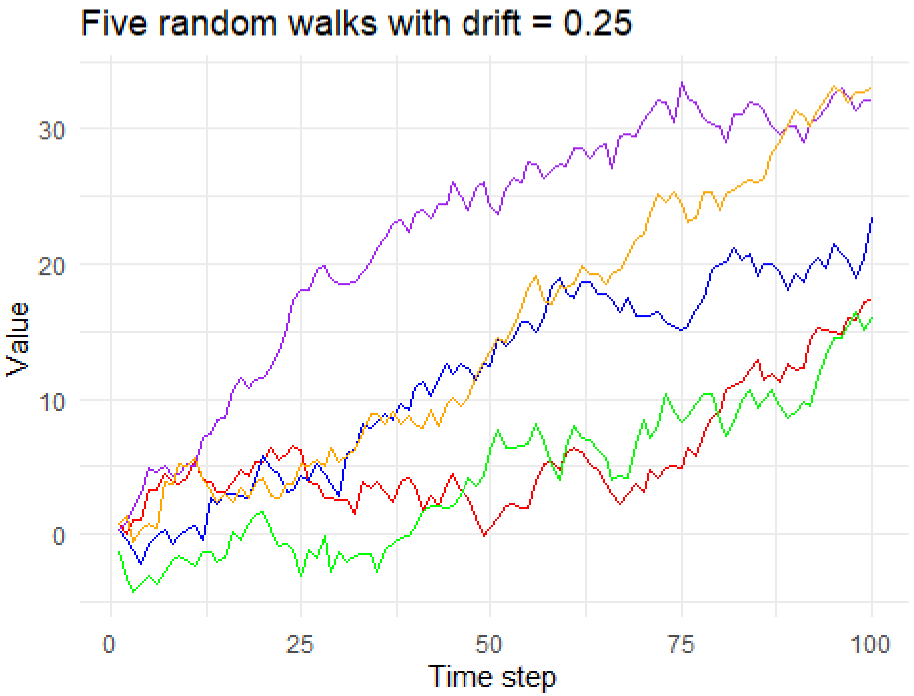
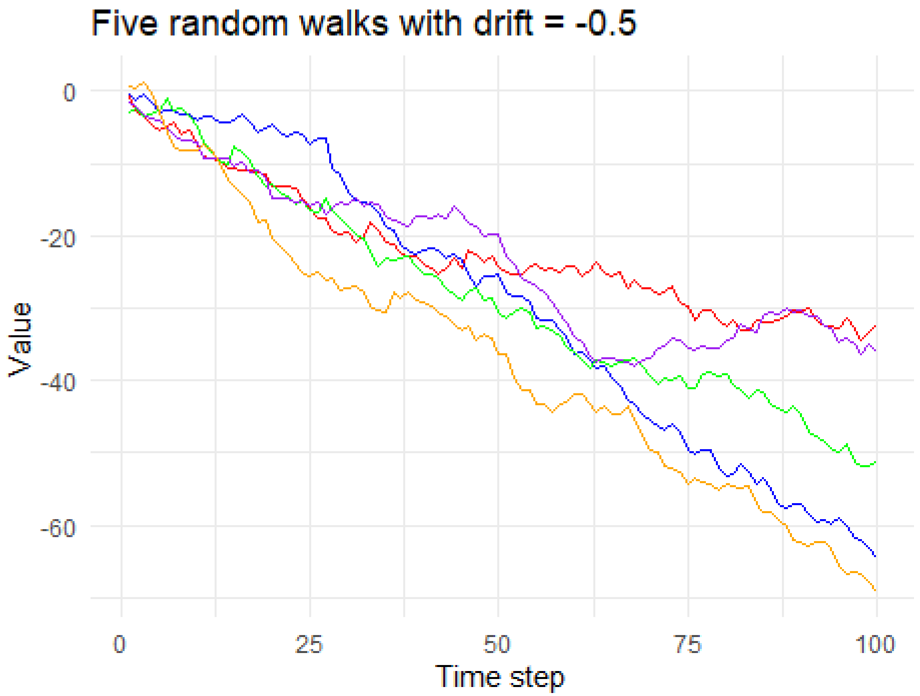
# Random Walk with Drift

- Random walk with drift c (the 1st difference does not have zero average):

$$y_t - y_{t-1} = c + \varepsilon_t \quad \text{or} \quad y_t = c + y_{t-1} + \varepsilon_t$$

- C is the average change between consecutive observations.



# Testing for Stationarity

- Unite root test  is a statistical test used to determine whether a time series has a unit root, which is a characteristic of a non-stationary time series
- There are several different unit root tests including:
    1. Augmented Dickey-Fuller (ADF) test.
    2. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

| Hypothesis Test | Null | Alternative | P-value to get stationarity |
|---|---|---|---|
| ADF | Non-Stationary | Stationary | Small |
| KPSS | Stationary | Non-Stationary | Large |

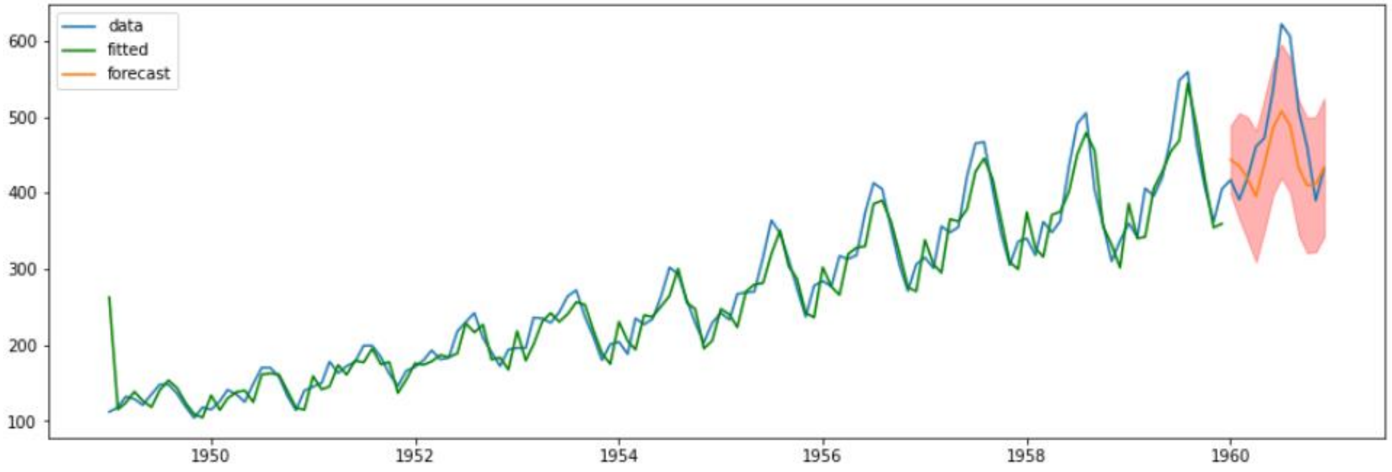
| | ADF | KPSS |
|---|---|---|
| ADF statistic | -12.533939 | 0.012944 |
| p-value | 0.0 | 0.1 |
| should we difference? | ? | |
| conclusion | | |

# Components of ARIMA model

1. Autoregressive (AR) term - captures the autocorrelation in the data
2. Integrated (I) term - removes the non-stationarity in the data
3. Moving Average (MA) term - captures the error term or noise in the data

How it works?

- The AR term models the current **value** of the time series as a linear combination of its past **values**.
- The I term models the differences between the current **value** and the past **value**.
- The MA term models the current **error** term as a linear combination of the past **error** terms.

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# Module 4 – Part II

# ARIMA models


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# Components of ARIMA model

ARIMA

1. Autoregressive (AR) term - captures the autocorrelation in the data
2. Integrated (I) term - removes the non-stationarity in the data
3. Moving Average (MA) term - captures the error term or noise in the data

# Autoregressive models

- An autoregressive (AR) model is a statistical model (multiple linear regression model) that uses lagged variable as predictors
- Autoregression = regression of the variable against itself
- AR(p) model, autoregressive model of order p.

$$\boxed{y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t}$$

- In AR(1) model:
  - when $\phi_1 = 0$ and $c = 0$, $y_t$ is equivalent to ?
  - when $\phi_1 = 1$ and $c = 0$, $y_t$ is equivalent to ?
  - when $\phi_1 = 1$ and $c \neq 0$, $y_t$ is equivalent to ?
  - when $\phi_1 < 0$, $y_t$ tends to oscillate around the mean.

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# Autoregressive Models (Example)

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

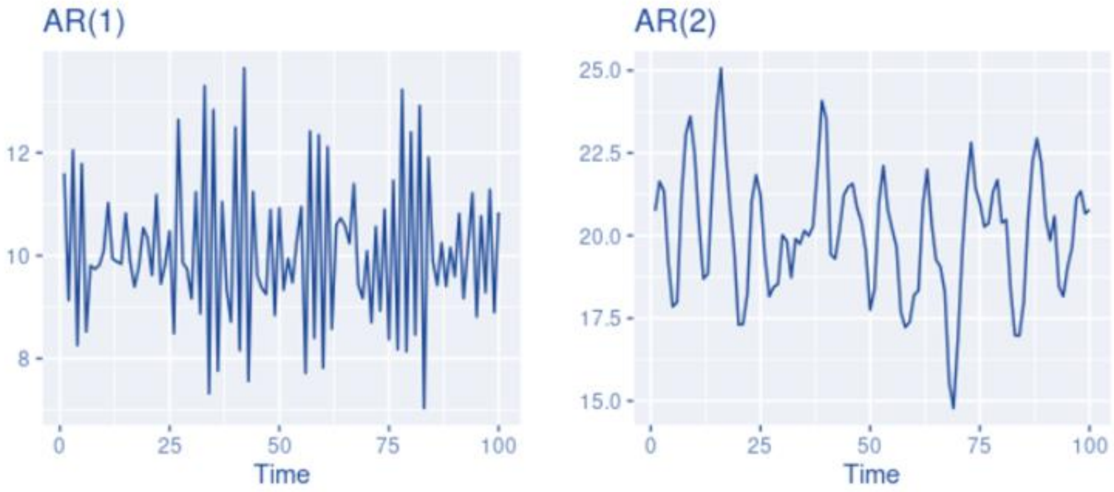


Figure 9.5: Two examples of data from autoregressive models with different parameters. Left: AR(1) with $y_t = 18 - 0.8y_{t-1} + \varepsilon_t$. Right: AR(2) with $y_t = 8 + 1.3y_{t-1} - 0.7y_{t-2} + \varepsilon_t$. In both cases, $\varepsilon_t$ is normally distributed white noise with mean zero and variance one.

# Moving Average Models

- A moving average model uses past forecast errors in a regression-like model
- MA(q) model, a moving average model of order q.

$$\boxed{y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}}$$

- $y_t$ can be thought of as a weighted moving average of the past few forecast errors
- We require $|\phi| < 1$ , the most recent observations carry a greater weight than those from the distant past.

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# Moving Average Models

$$\boxed{y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}}$$

- Do NOT confuse this model with simple moving average method or exponentially weighted moving average method.
- Moving average models is used for forecasting future values!
- Moving average smoothing (SMA, EWMA, …) is used for estimating the trend-cycle of past values.

# Moving Average Models (Example)

$$\boxed{y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}}$$

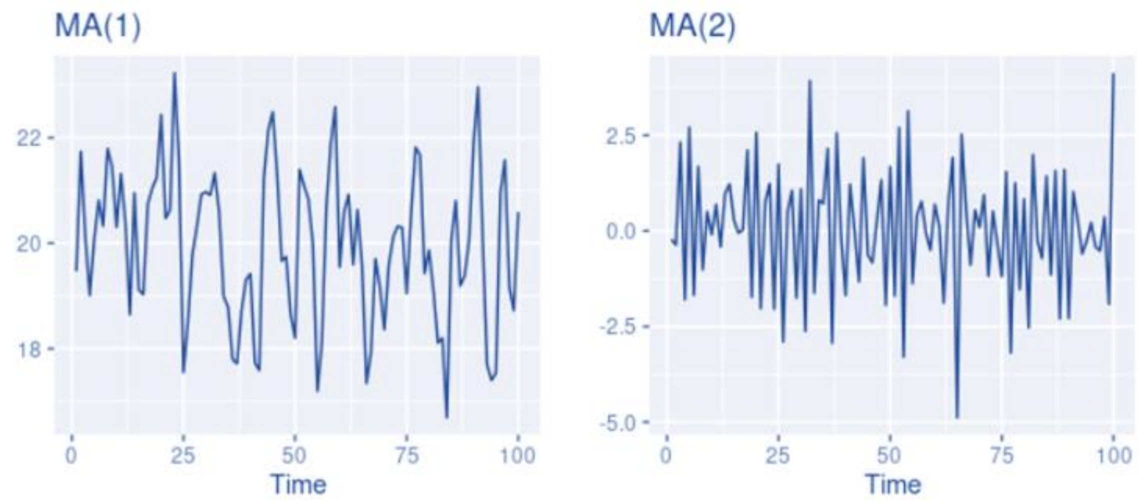


Figure 9.6: Two examples of data from moving average models with different parameters. Left: MA(1) with $y_t = 20 + \varepsilon_t + 0.8\varepsilon_{t-1}$. Right: MA(2) with $y_t = \varepsilon_t - \varepsilon_{t-1} + 0.8\varepsilon_{t-2}$. In both cases, $\varepsilon_t$ is normally distributed white noise with mean zero and variance one.

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# ARIMA (AutoRegressive Integrated Moving Average)

- ARIMA model combines three models, autoregressive (AR) model, an integrated (I) model, and a moving average (MA) model.
- ARIMA(p, d, q) model.

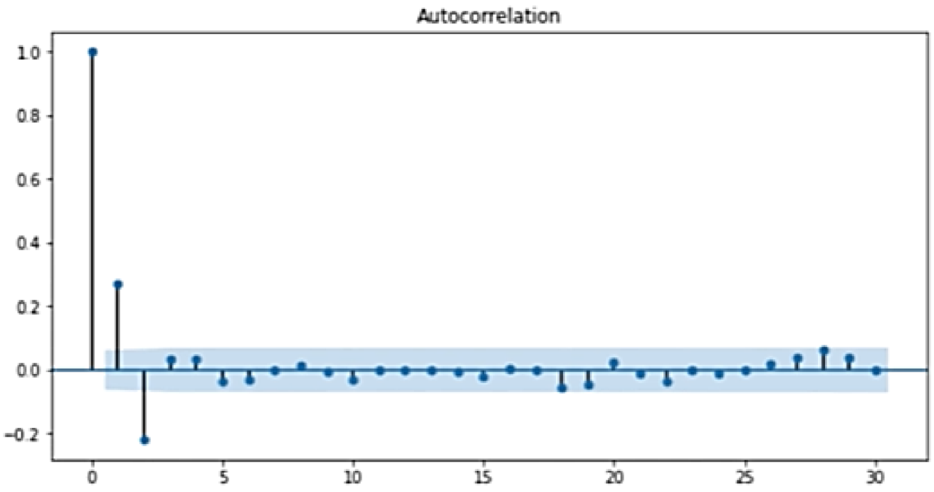
$$\boxed{y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t}$$

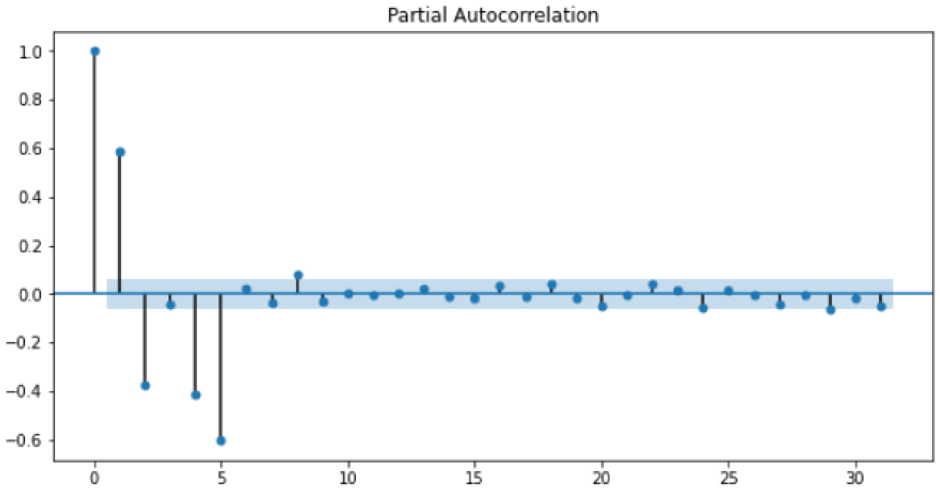
- $y'_t$ is the differenced time series.
- d degree of first difference involved.
- Note: p, d, and q are estimated using MLE.

| | |
|---|---|
| ? | ARIMA(0,0,0) with no constant |
| ? | ARIMA(0,1,0) with no constant |
| ? | ARIMA(0,1,0) with a constant |
| ? | ARIMA($p$,0,0) |
| ? | ARIMA(0,0,$q$) |

# Selecting (p, q) orders using ACF and PAC

- Some rough guidelines:
- Identification of an AR model is often best done with the PACF
  - p set to be the maximum significant non-zero lag in PACF typically followed by a sharp decline.
- Identification of an MA model is often best done with the ACF
  - q set to be the maximum significant non-zero lag in ACF typically followed by a sharp decline.

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# Model selection

- Fore model selection we can either use information criteria or any cross validated performance metrics like $R^2$, MSE, RMSE, MAPE, sMAPE.

| Information Criteria | Formula |
| --- | --- |
| Akaike's Information Criterion (AIC) | $\text{AIC} = -2\log(L) + 2k$ |
| AIC corrected for small sample bias (AICc) | $\text{AIC}_{\text{c}} = \text{AIC} + \frac{2k(k+1)}{T-k-1}$ |
| Bayesian Information Criterion (BIC) | $\text{BIC} = \text{AIC} + k[\log(T) - 2]$ |

- L is the likelihood of the model and K is the total number of parameters (including the variance of residuals)
- The model with the minimum information criteria is often the best model for forecasting

# SARIMA (Seasonal ARIMA) models

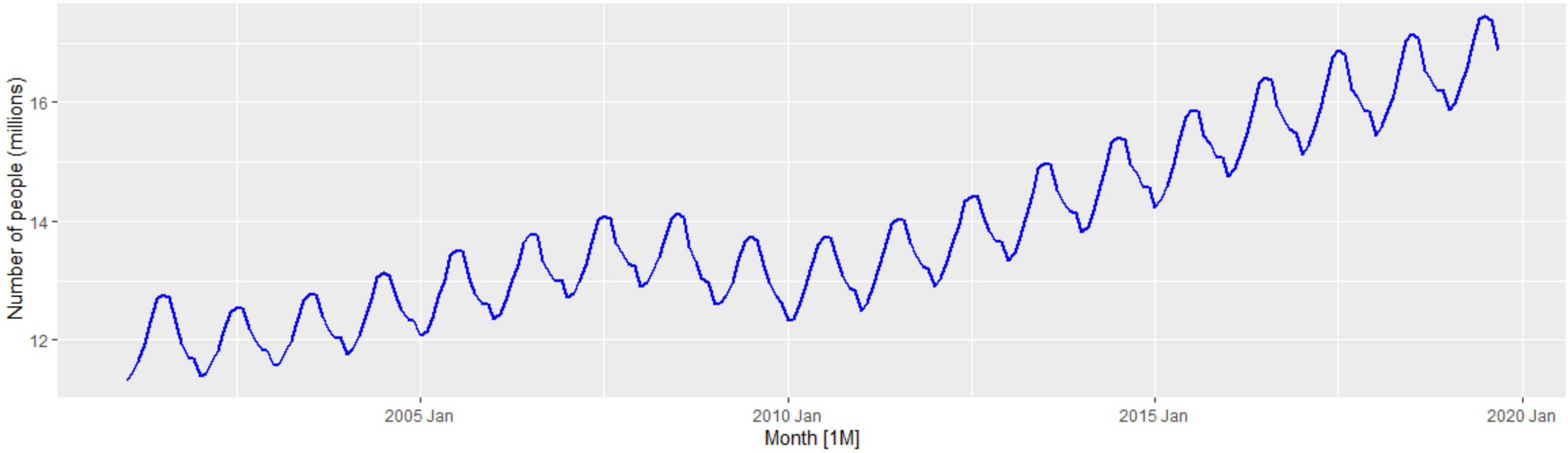
- SARIMA is an extension of an ARIMA model that includes additional seasonal terms.
- It is used to model time series data that exhibits seasonal patterns

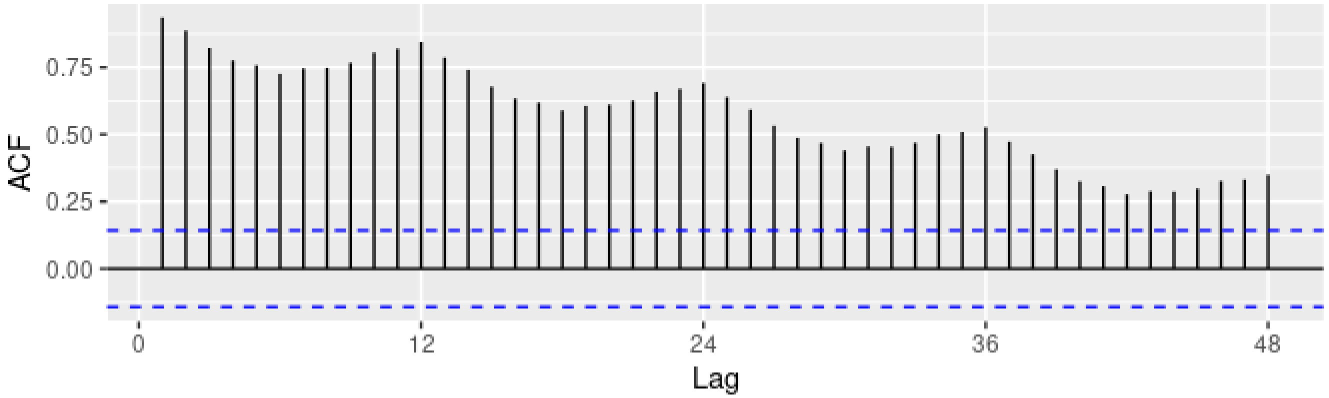
$$\text{ARIMA} \quad \underbrace{(p, d, q)}_{\substack{\uparrow \\ \text{Non-seasonal part} \\ \text{of the model}}} \quad \underbrace{(P, D, Q)_m}_{\substack{\uparrow \\ \text{Seasonal part} \\ \text{of the model}}}$$

- p, d, q are defined as before.
- P is the order of the seasonal autoregressive component
- D is the degree of seasonal differencing
- Q is the order of the seasonal moving average component
- m is the period of the seasonality. m = 4, 12 is for quarterly and monthly seasonality, respectively.

# SARIMA example

Monthly US leisure and hospitality employment, 2001-2019.

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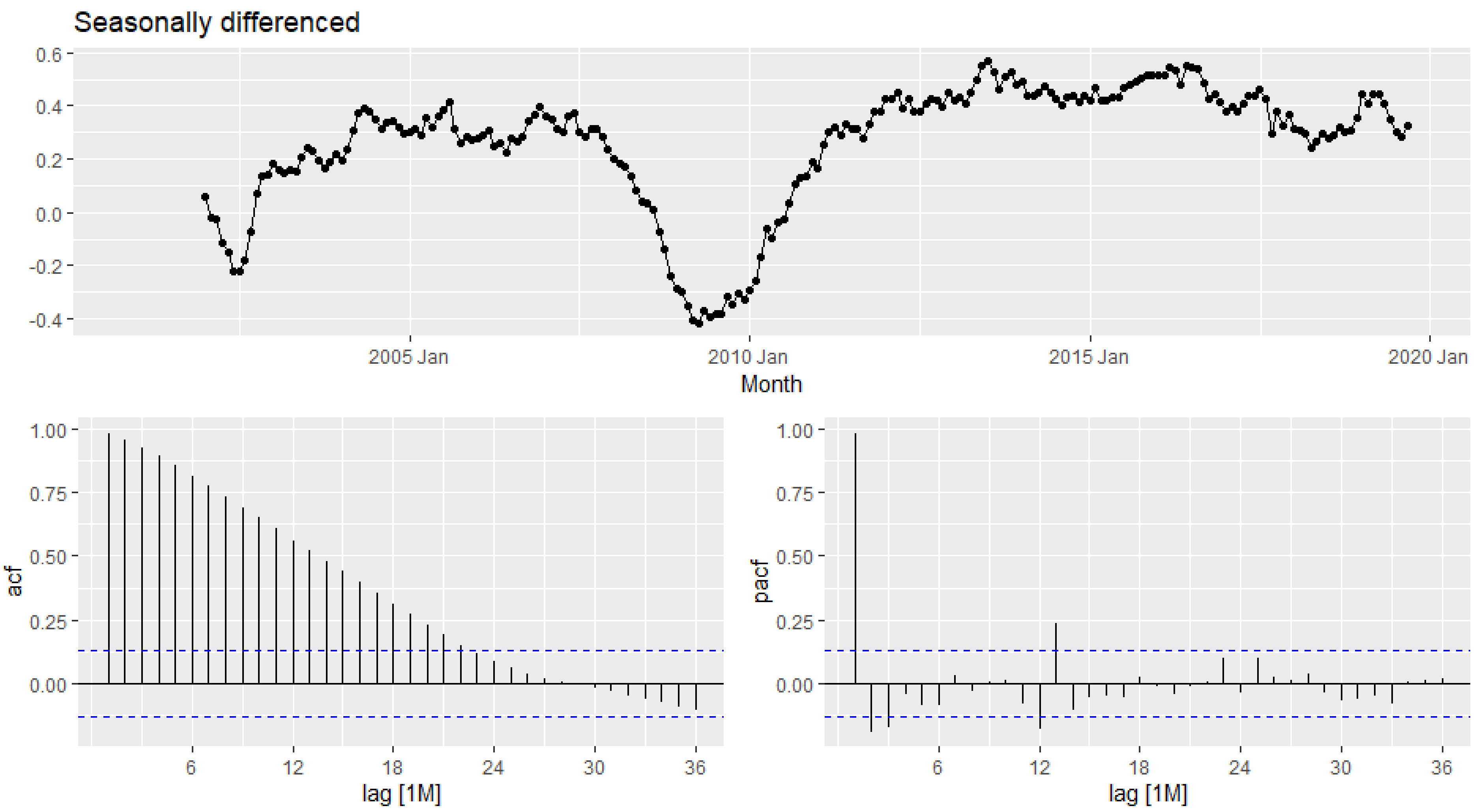
# SARIMA example

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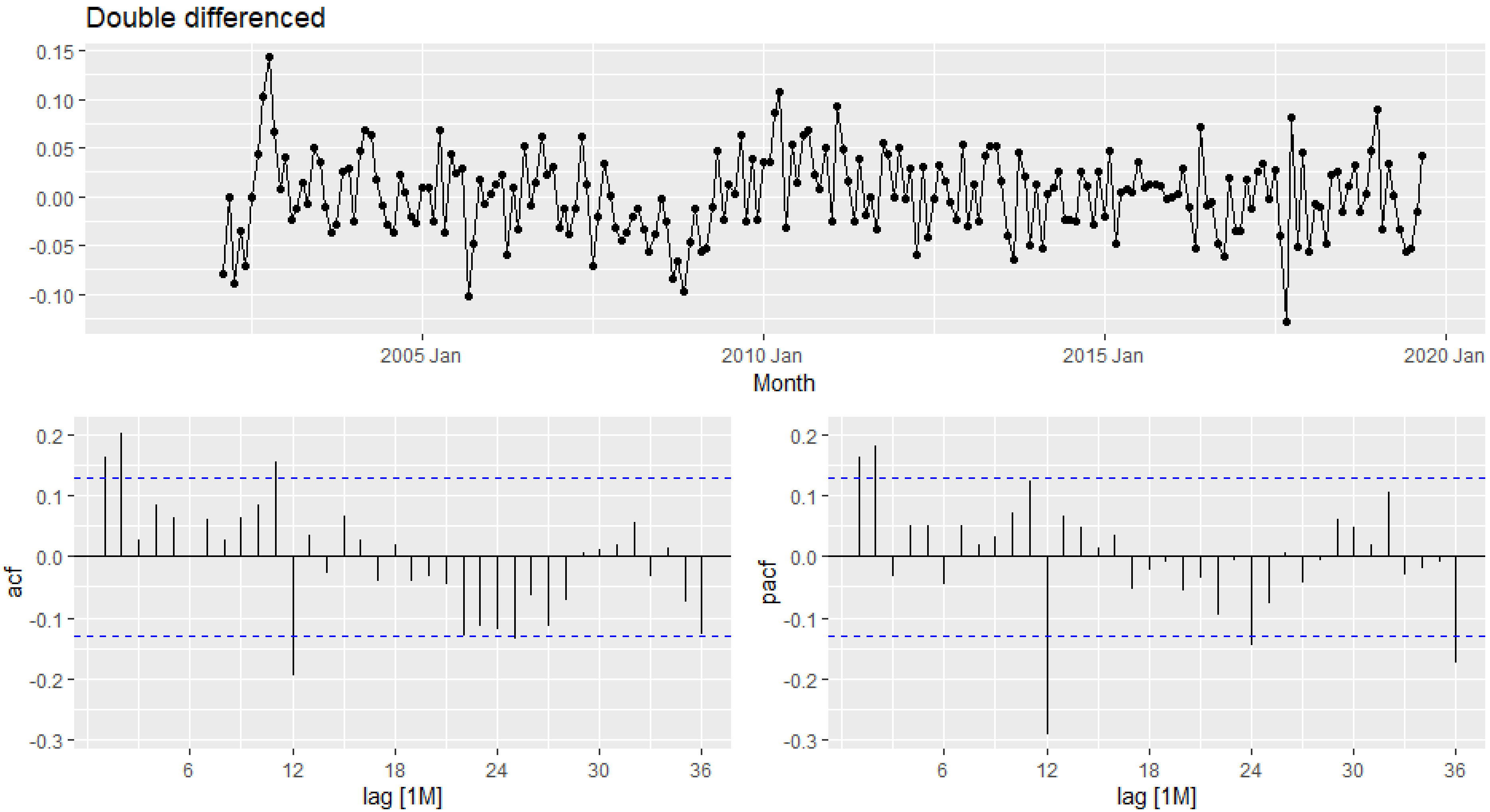
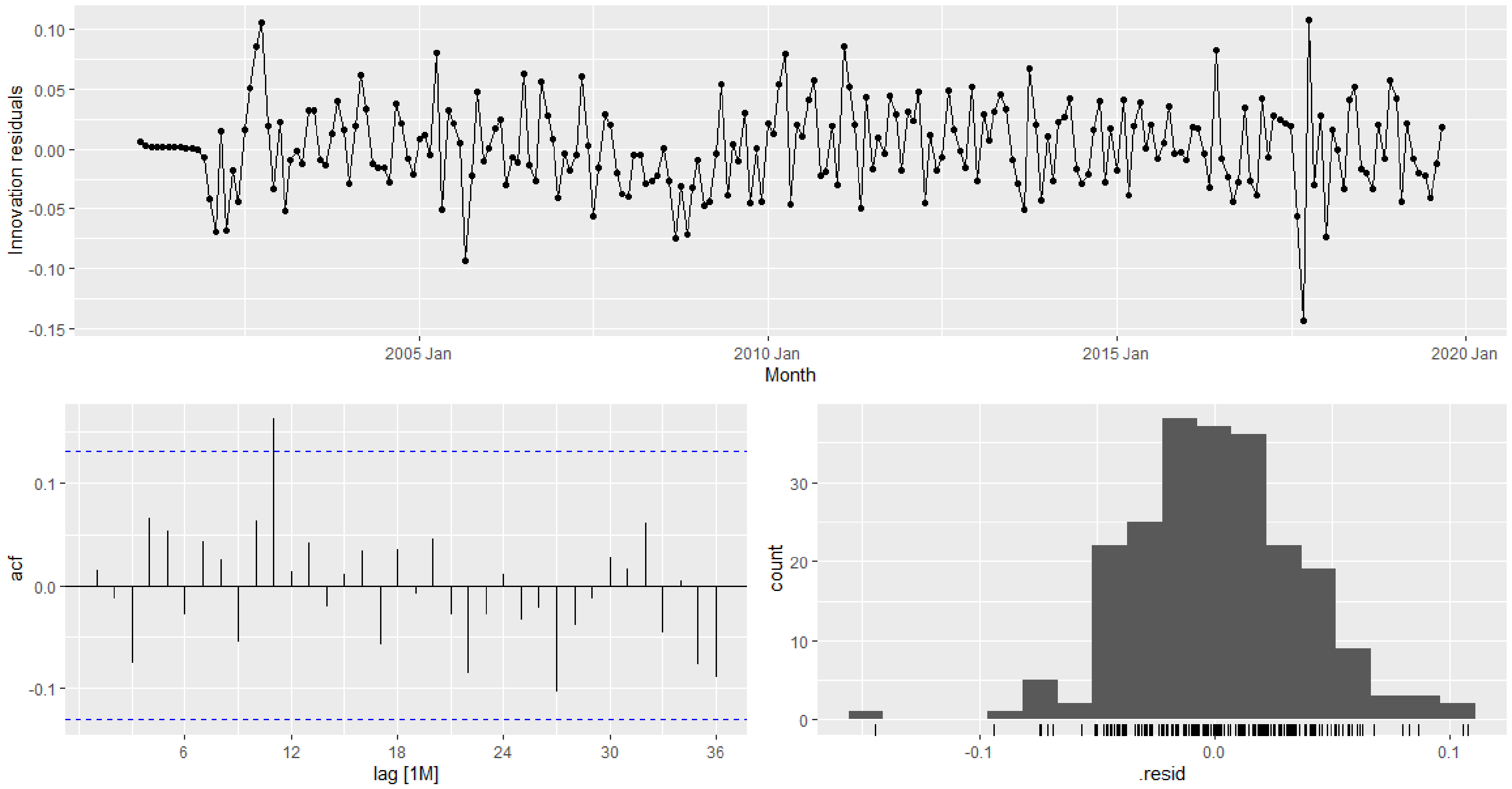
# SARIMA example



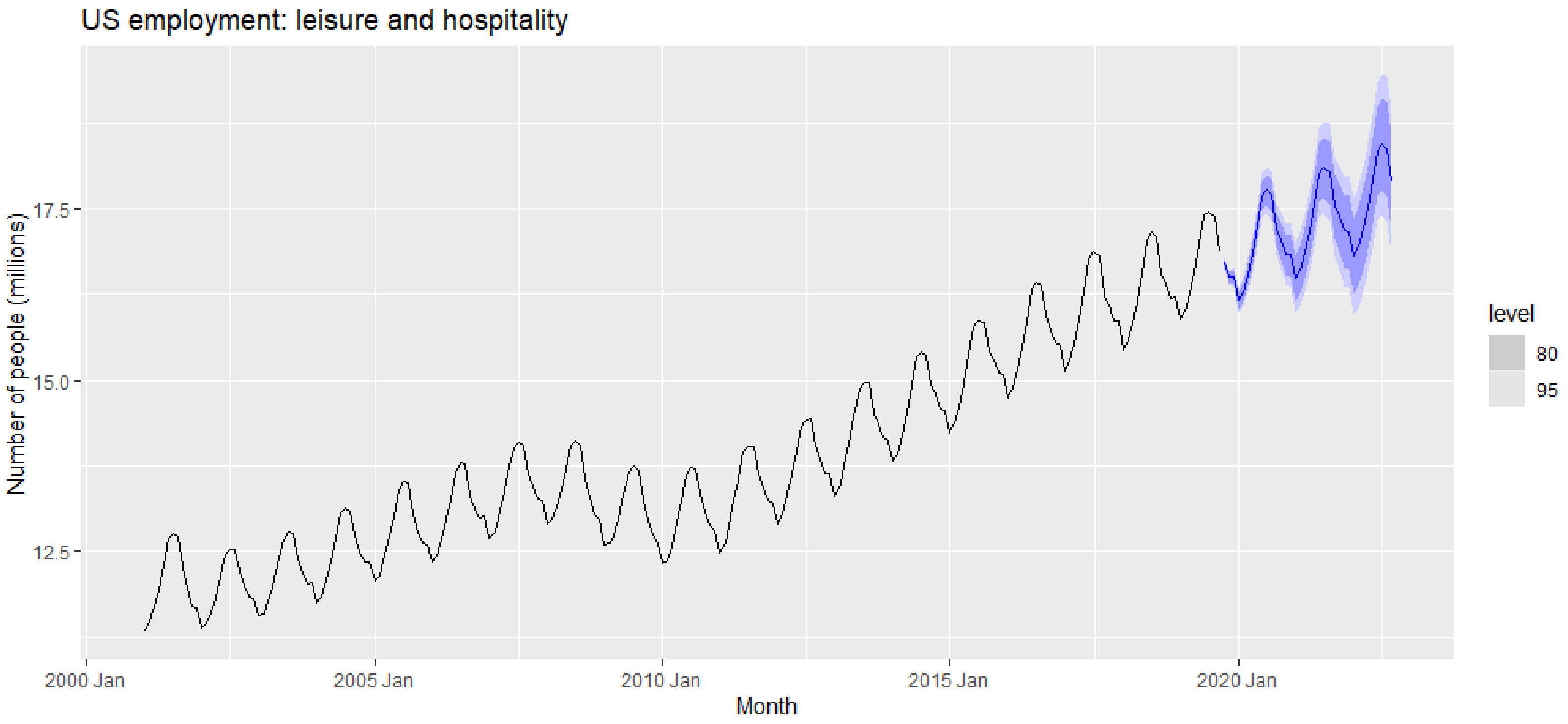
# SARIMA example

- Using Auto-SARIMA, the winning model is $\text{SARIMA}(2,1,0)(1,1,1)_{12}$
- Plotting residuals to confirm they are like Gaussian white noise.

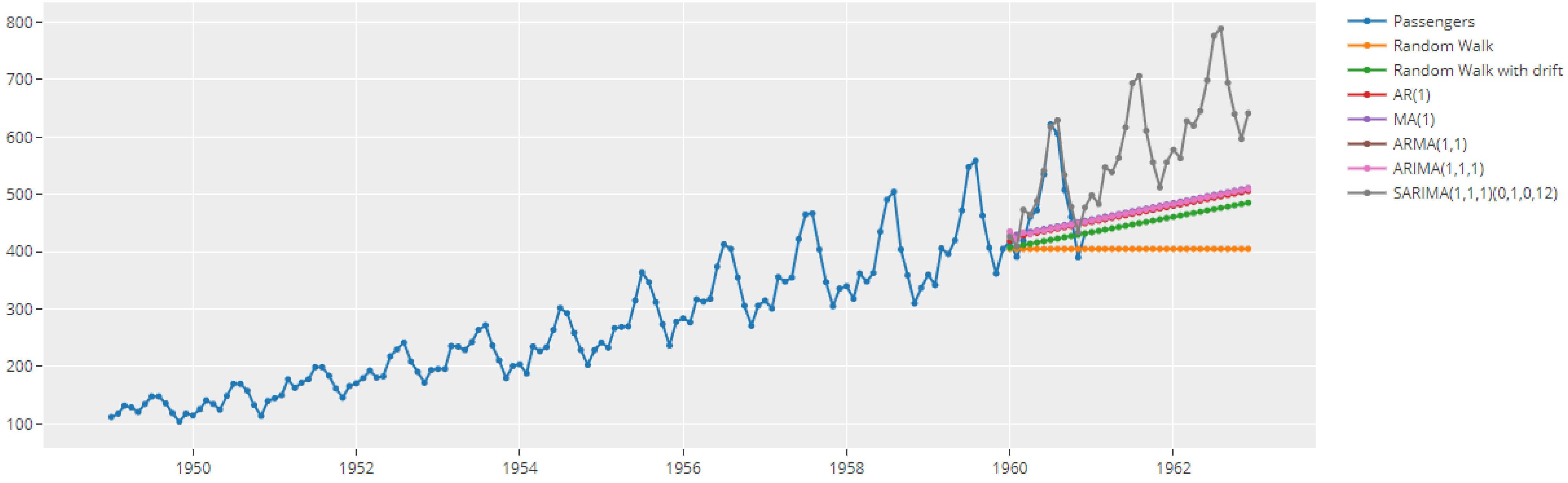


# SARIMA example, Forecasting

- We now have a seasonal ARIMA model that passes the required checks and is ready for forecasting.
- The forecasts have captured the seasonal pattern very well, and the increasing trend extends the recent pattern. The trend in the forecasts is induced by the double differencing.



# Comparing all the models



# ARIMA: Advantages and Disadvantages

- Flexible and can be used with a wide range of time series data.
- Able to capture both linear and non-linear relationships
- Easy to implement and interpret

- Difficult to tune and get accurate forecasts, especially for time series with complex patterns or multiple seasonality
- It is sensitive to the choice of parameters and can produce unstable forecasts if the parameters are not chosen carefully.

# Road map!

✓ Module 1- Introduction to Deep Forecasting

✓ Module 2- Setting up Deep Forecasting Environment

✓ Module 3- Exponential Smoothing

✓ Module 4- ARIMA models

- Module 5- Machine Learning for Time series Forecasting
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