9

Short-Term Forecasting with ARIMA Models

All models are wrong, some are useful

GEORGE E. P. BOX (1919 – 2013)

In this chapter, we introduce a class of techniques, called ARIMA (for Auto-Regressive Integrated Moving Average), which can be used to describe stationary time series and nonstationary time series with changing levels. For seasonal time series, the nonstationary ARIMA process is extended to account for a multiplicative seasonal component. These models form the framework for

- expressing various forms of stationary (level) and nonstationary (mostly trending and seasonal) behavior in time series
- producing optimal forecasts with prediction limits for a time series from its own current and past values
- developing a practical and useful modeling process

The topics covered include:

- what an ARIMA forecasting model is used for
- why stationarity is an important concept for ARIMA processes
- how to select ARIMA models through an iterative three-stage procedure
- how, when, and why we should use the Box Jenkins modeling methodology for ARIMA forecasting models
- its relationship to the modern State Space forecasting methodology
Why Use ARIMA Models for Forecasting?

In chapter 2, we constructed a year-by-month ANOVA table as an exploratory, data-driven technique for examining trend and seasonal variation in a time series. This led us to estimate many coefficients for the monthly and yearly means in the rows and columns of a table. (e.g., In Excel, run Data Analysis Add in > Anova: Two factor without replication). Although the results were not intended for generating projections, the ANOVA table provides a useful preliminary view of the data. Figure 9.1 shows (a) a time plot of the classical Series G Box-Jenkins airline passenger miles data and (b) pie chart representing the contribution in the total variation due to Seasonality (83%), Trend (14%) and Other (3%). These data consists of monthly totals of airline passengers from January 1949 to December 1960.

![Figure 9.1](image-url)

The ARIMA modeling approach offers a model-driven technique to time series forecasting by using a theoretical framework developed by George E.P. Box (1919– 2013) and Gwilym M. Jenkins (1932– 1982). The theory was first published in a seminal book titled *Time Series Analysis – Forecasting and Control* (1976).

Many studies have shown that forecasts from simple ARIMA models have frequently outperformed larger, more complex econometric systems for a number of economic series. Although it is possible to construct ARIMA models with only 2 years of monthly historical data, the best results are usually obtained when at least 5 to 10 years of data are available - particularly for seasonal time series.

A significant advantage of univariate ARIMA approach is that useful models can be developed in a relatively short time with automated State Space Forecasting algorithms. Therefore, a practitioner can often deliver significant results with ARIMA modeling early in a project for which adequate historical data exist. Because of the sound theoretical underpinnings, the demand forecaster should always consider ARIMA models as an important forecasting tool whenever these models are relevant to the problem at hand.
A drawback of univariate models is that they have limited explanatory capability. The models are essentially sophisticated extrapolative devices that are of greatest use when it is expected that the underlying factors causing demand for products, services, revenues, and so on, will behave in the future in much the same way as in the past. In the short term, this is often a reasonable expectation, however, because these factors tend to change slowly; data tend to show inertia in the short term. However, there are extensions of the ARIMA approach that incorporate explanatory factors for including information such as price, promotions, strikes, and holiday effects. These models are called transfer function (or dynamic regression) models, but are beyond the scope of this book.

Much more time is usually required to obtain and validate historical data than to build the models. Therefore, a practitioner can often deliver significant results with ARIMA modeling early in a project for which adequate historical data exist. The forecaster should always consider ARIMA models as an important option in a forecasting toolbox whenever trend/seasonal models are relevant to the problem at hand.

**The ARIMA models have proved to be excellent short-term forecasting models for a wide variety of time series.**

The Linear Filter Model as a Black Box
The application of ARIMA models is based on the idea that a time series in which successive values are highly dependent (i.e. having “memory” of the past values) can also be thought of as having come from a process involving a series of independent errors or shocks, \( \varepsilon_t \). The general form of a (discrete) linear process is:

\[
Z_t = \mu + \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \ldots + \psi_n \varepsilon_{t-n} + \ldots
\]

where \( \mu \) and all \( \psi_j \) are fixed parameters and the \( \{ \varepsilon_t \} \) is a sequence of identically, independently distributed random errors with zero mean and constant variance.

Why is it called a linear filter? The process is linear because \( Z_t \) is represented as a linear combination of current and past shocks. It is often referred to as a black box or filter, because the model relates a random input to an output that is time dependent. The input is filtered, or damped, by the equation so that what comes out of the equation has the characteristics that are wanted.

Figure 9.2 Black-box representation of the linear random process.

A linear process can be visualized as a black box as follows (Figure 9.2). White noise or purely random error \( \{ \varepsilon_t \} \) is transformed to an observed series \( \{ Y_t \} \) by the operation of a linear filter; the filtering operation simply takes a weighted sum of previous shocks. For convenience, we henceforth write models in terms of \( Y_t \), which has been mean adjusted, that is, \( Y_t = Z_t - \mu \). The weights are known as \( \psi \) (psi) coefficients. For \( Y_t \) to represent a valid stationary process, it is necessary that the coefficients \( \psi_j \) satisfy the condition \( \sum \psi_j^2 < \infty \).
A linear process is capable of describing a wide variety of practical forecasting models for time series. It can be visualized as a black-box equation transforming random inputs into the observed data.

It can be shown that any linear process can be written formally as a weighted sum of the current error term plus all past shocks. In many problems, such as those in which it is required that future values of a series be predicted; it is necessary to construct a parametric model for the time series. To be useful, the model should be physically meaningful and involve as few parameters as possible. A powerful parametric model that has been widely used in practice for describing empirical time series is called the mixed autoregressive moving-average (ARMA) process:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

where $p$ is the highest lag associated with the data, and $q$ is the highest lag associated with the error term. The ARMA processes are important because they are mathematically tractable and they are capable of providing prediction limits for uncertainty measurement. The inputs to the black box (Figure 9.3) are the shocks $\varepsilon_t$ and the output is the observed historical data or time series $Z_t$.

There are some special versions of the ARMA process that are particularly useful in practice. If that weighted sum has only a finite number of nonzero error terms, then the process is known as a moving average (MA) process. It can be shown that the linear process can also be expressed as a weighted sum of the current shock plus all past observed values. If the number of nonzero terms in this expression is finite, then the process is known as an autoregressive (AR) process. The origin of the AR and MA terminology are described a little later with specific examples.

Figure 9.3 Black-box representation of the ARMA process (with a nonstationary filter).

It turns out that an MA process of finite order can be expressed as an AR process of infinite order and that an AR process of finite order can be expressed as an MA process of infinite order. This duality has led to the principle of parsimony in the Box-Jenkins methodology, which recommends that the practitioner employ the smallest possible number of parameters for adequate representation of a model. In practice, it turns out that relatively few parameters are needed to make usable forecasting models with business data.

It may often be possible to describe a stationary time series with a model involving fewer parameters than either the MA or the AR process has by itself. Such a model will possess qualities of both autoregressive and moving average models: it is called an ARMA process. An ARMA (1, 1) process, for example, has one prior observed-value term of lag 1 and one prior error term:

$$Y_t = \phi_1 Y_{t-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1}$$

The general form of an ARMA $(p, q)$ process of autoregressive order $p$ and moving average order $q$ looks like:
\[ Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \]

In short, the ARMA process is a linear random process. It is linear if \( Y_t \) is a linear combination of lagged values of \( Y_t \) and \( \varepsilon_t \). It is random if the errors (also called shocks or disturbances) are introduced into the system in the form of white noise. The random errors are assumed to be independent of one another and to be identically distributed with a mean of zero and a constant variance \( \sigma^2 \).

The ARMA process is important because it is mathematically tractable and can be shown to produce a wide variety of useful forecasting profiles for time series.

### A Model-Building Strategy

The Box-Jenkins approach for ARIMA modeling provides the demand forecaster with a very powerful and flexible tool. Because of its complexity, it is necessary to establish procedures for coming up with practical models. Its difficulty requires a fair amount of sophistication and judgment in its use. Nevertheless, its proven results in terms of forecasting accuracy and understanding processes generating data and forecast accuracy can be invaluable in the hands of a skilled user.

The Box-Jenkins procedure consists of the following three stages.

1. **Identification** consists of using the data and any other knowledge that will tentatively indicate whether the time series can he described with a moving average (MA) model, an autoregressive (AR) model, or a mixed autoregressive – moving average (ARMA) model.
2. **Estimation** consists of using the data to make inferences about the parameters that will be needed for the tentatively identified model and to estimate values of them.
3. **Diagnostic checking** involves the examination of residuals from fitted models, which can result in either no indication of model inadequacy or model inadequacy, together with information on how the series may be better described.

The procedure is iterative. Thus, residuals should be examined for any lack of randomness and, if we find that residuals are serially correlated, we use this information to modify a tentative model. The modified model is then fitted and subjected to diagnostic checking again until an adequate model is obtained.

Although a Box-Jenkins methodology is an excellent way for forecasting a time series from its own current and past values, it should not be applied blindly and automatically to all forecasting problems.

### Identification: Interpreting Autocorrelation and Partial Autocorrelation Functions

The primary tool for identifying an ARMA process is with autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs). ACFs are quantities used for describing the mutual dependence among values in a time series.

Extreme care should be taken in interpreting ACFs, however; the interpretation can be complex and requires some ongoing experience with real data. Attention should be directed to individual values as well as to the overall pattern of the autocorrelation coefficients. In practice, the autocorrelations of low-order ARMA processes are used to help identify models with the Box-Jenkins methodology.

Autocorrelation analysis can be a powerful tool for deciding whether a process shows pure autoregressive behavior or moving average behavior in ARMA models.
Autocorrelation and Partial Autocorrelation Functions

The ACF and PACF are widely used in identifying ARMA models. The corresponding ordinary and partial correlograms are the sample estimates of the ACF and PACF. They play an important role in the identification phase of the Box-Jenkins methodology for forecasting and control applications. Some examples follow, but to simplify writing model equations, we use a notational device known as the backshift operation.

For example, the ACF of an AR (1) process is depicted in Figure 9.4. There is a decaying pattern in the ACF; the decay is exponential if $0 < \phi_1 < 1$ (Figure 9.4a). For $-1 < \phi_1 < 0$ (Figure 9.4b), the ACF is similar but alternates in sign. The PACF shows a single positive value at lag 1 if $0 < \phi_1 < 1$ and a negative spike at lag 1 if $-1 < \phi_1 < 0$.

![Figure 9.4](image)

Figure 9.4 (a) ACF an AR (1) process ($\phi_1 = 0.70$); (b) ACF of an AR (1) process ($\phi_1 = -0.80$).

The PACF is more complex to describe. It measures the correlation between $Y_t$ and $Y_{t-k}$ adjusted for the intermediate values $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-k+1}$ (or the correlation between $Y_t$ and $Y_{t-k}$ not accounted for by $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-k+1}$). If we denote by $\phi_{kj}$ the $j$th coefficient in an AR($k$) model, so that $\phi_{kk}$ is the last coefficient, then it can be shown that the $\phi_{kj}$ will be nonzero for $k \leq p$ and zero for $k > p$, where $p$ is the order of the autoregressive process. Another way of saying this is that $\phi_{kk}$ has a cutoff or truncation after lag $p$. For example, the PACF of an AR (1) process has one spike at lag 1. It has the value $\phi_1$.

Another basic process that occurs fairly often in practice is the AR (2) process. In this case there are two autoregressive coefficients $\phi_1$ and $\phi_2$. Figure 9.5 shows the ACF and PACF of an AR (2) model with $\phi_1 = 0.3$ and $\phi_2 = 0.5$. The PACF shows positive values at lags 1 and 2 only. The PACF is very helpful because it suggests that the process is autoregressive and, more important, that it is second-order autoregressive.
Figure 9.5 (left) ACF and (right) PACF of an autoregressive AR (2) model with parameters $\phi_1 = 0.3$ and $\phi_2 = 0.5$.

Figure 9.6 (left) ACF and (right) PACF of an autoregressive AR (2) model with parameters $\phi_1 = 1.2$ and $\phi_2 = -0.64$.

If $\phi_1 = 1.2$ and $\phi_2 = -0.64$, the ACF and PACF have the patterns shown in Figure 9.6. The values in the ACF decay in a sinusoidal pattern; the PACF has a positive value at lag 1 and a negative value at lag 2. There are a number of possible patterns for AR (2) models. A triangular region describes the allowable values for $\phi_1$ and $\phi_2$ in the stationary case: $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$, and $-1 < \phi_2 < 1$. If $\phi_1^2 + 4\phi_2 > 0$, the ACF decreases exponentially with increasing lag. If $\phi_1^2 + 4\phi_2 < 0$, the ACF is a damped cosine wave.

Figure 9.7 (a) ACF and (b) PACF of a MA (1) model with positive parameter $\theta$.
The ACF of a MA (q) process is 0, beyond the order q of the process (i.e., it has a cutoff after lag q). For example, the ACF of a MA (1) process has one spike at lag 1, the others are 0. It has the value $\rho_1 = -\frac{\theta_1}{1 + \theta_1^2}$ with $|\rho_1| \leq \frac{1}{2}$.

The PACF of the MA process is complicated, so in Figure 9.7 we display the ACF and PACF of an MA (1) model with positive $\theta_1$. There is a single negative spike at the lag 1 in the ACF. There is a decaying pattern in the PACF. The ACF of an MA(1) process with negative $\theta$ (Figure 9.8) shows a single positive spike, but the PACF shows a decaying pattern with spikes alternating above and below the zero line.

Figure 9.8 (a) ACF and (b) PACF of a MA (1) model with negative parameter $\theta$.  

**An Important Duality Property**

One important consequence of the theory is that the ACF of an AR process behaves like the PACF of an MA process and vice versa. This aspect is known as a duality property of the AR and MA processes. If both the ACF and the PACF attenuate, then a mixed model is called for.

It turns out that the ACF of the pure MA (q) process truncates, becoming 0 after lag q, whereas that for the pure AR (p) process is of infinite extent. MA processes are thus characterized by truncation (spikes ending) of the ACF, whereas AR processes are characterized by attenuation (gradual decay) of the ACF. Derivations of this kind are beyond the scope of this book.

For an AR process, the ACF attenuates and the PACF truncates; conversely, for an MA process, the PACF attenuates and the ACF truncates.

The mixed ARMA (p,q) model contains p AR coefficients ($\phi_1, \phi_2 \ldots \phi_p$) and q MA coefficients ($\theta_1, \theta_2, \ldots, \theta_q$). This model is useful in that stationary series may often be expressed more parsimoniously (with fewer parameters) in an ARMA model than as a pure AR or pure MA model. In practice, for mixed ARMA processes, you should create a catalog of ACF and PACF patterns to establish the orders p and q of the autoregressive and moving average components. The estimated autocorrelation functions, or correlograms, are then matched with the cataloged patterns in order to establish a visual identification of the most useful model for a given situation. Usually, more than one model suggests itself, so that we may tentatively identify several similar models for a particular time series.

Some useful rules for identification are:

- If the correlogram cuts off at some point, say $k = q$, then the appropriate model is MA (q).
- If the partial correlogram cuts off at some point, say $k = p$, then the appropriate model is AR (p).
• If neither diagram cuts off at some point, but does decay gradually to zero, the appropriate model is ARMA (p’, q’) for some p’, q’.

The ACF and PACF of an ARMA (p, q) model are more complex than either the AR (p) or MA (q) models. The ACF of an ARMA (p, q) process has an irregular pattern at lags 1 through q, then the tail diminishes. The PACF tail also diminishes.

The best way to identify an ARMA process initially is to look for decay or a tail in both the ACFs and PACFs.

The complete chapter can be found in

Change & Chance Embraced

ACHIEVING AGILITY WITH DEMAND

FORECASTING IN THE SUPPLY CHAIN

HANS LEVENBACH, PhD
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Is Demand Forecasting Worthwhile?
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Demand Forecasting Is Mostly about Data

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