Predicting Model to the Wholesale & Retail Trade, Restaurants & hotels GDP IN KSA

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Abstract:

In this research, use the time series models Gross domestic product (GDP) at current price in KSA Wholesale & Retail Trade, Restaurants & hotels. The results showed that the model is the appropriate model for the series of Arima is: ARIMA (2,1,0)
According to the estimation results of this model, we observe the compatibility between observed and estimated values as these values are consistent with those in the original time series, indicating the strength of the model and predictability. We see the agreement between the real and estimated values in light of the model's estimation findings, which highlights its predictive strength. The model is regarded as the best among all the selected models since it outperformed all the requirements for time series, had a high level of predictive ability, and has predicted values that are comparable to and close to the original values. For the descriptive statistics of the model, R-squared represents the coefficient of good fit if the value is greater = 0.82 more than 0.05 this mean the model represent data exactly (good model) . This table provides an estimate of the coefficients of the model, from the model we note that the level of significance Sig= 0.00. Less than 0.05, which indicates that the coefficients are statistically significant, also effective and predictable .
Key words : Autocorrelation; Moving Average; Partial Autocorrelation ; estimation.

المستخلص:

في هذا البحث تم استخدم نماذج السلاسل الزمنية لبيانات الناتج المحلي الإجمالي بالسعر الحالي لبيانات تجارة الجملة والتجزئة والمطاعم والفنادق في المملكة العربية السعودية . أظهرت النتائج أن النموذج هو النموذج المناسب لسلسلة نموذج أريما هو: اريما (٢,١,٠)

وفقًا لنتائج التقدير لهذا النموذج ، نلاحظ التوافق بين القيم الحقيقية والمقدرة مما يشير إلى قوة النموذج والقدرة على التنبؤ. حيث تمت مقارنة النموذج مع العديد من نماذج السلاسل الزمنية ، وحقق كل الشروط الخاصة بالسلاسل الزمنية ، حيث اثبت قدرته العالية على التنبؤ ، وان قيمه التنبؤية مشابهة ومقاربة للقيم الأصلية ويعتبر الأفضل من بين كل النماذج المختارة . بالنسبة للإحصاءات الوصفية للنموذج ، يمثل R-squared معامل التحديد ٠,٨٢ وهذا يعني أن النموذج يمثل البيانات تمثيلاً صادقاً (نموذج جيد). ومن تقديرًا لمعاملات النموذج نلاحظ أن مستوى المعنوية Sig = 0.00. أقل من ٠,٠٥ ، مما يشير إلى أن المعاملات ذات دلالة إحصائية.

Introduction

Autoregressive Moving Average Model (ARMA) is a statistical model that analyses and forecasts time series data. In the early 1950s, mathematician and statistician George Box and his friend Gwilym Jenkins developed the ARMA model. The ARMA model is an extension of the autoregressive (AR) model and the moving average (MA) model, both simpler ways to look at time series. The AR component models the relationship between a time series and its past values.

The MA component models the relationship between a time series and its past error terms. By combining these two components in the ARMA model, analysts can create a flexible model that can capture a wide range of time series patterns and trends. The parameters p and q represent the orders (number of lags) of the AR and MA components, respectively, and can be chosen based on data-driven methods and domain expertise.

Choose p and q

The orders p and q can be chosen based on various data-driven methods, such as the following:

- autocorrelation function (ACF)
- partial autocorrelation function (PACF)
- extended autocorrelation function (EACF)
- Akaike Information Criterion (AIC)
- Bayesian Information Criterion (BIC)

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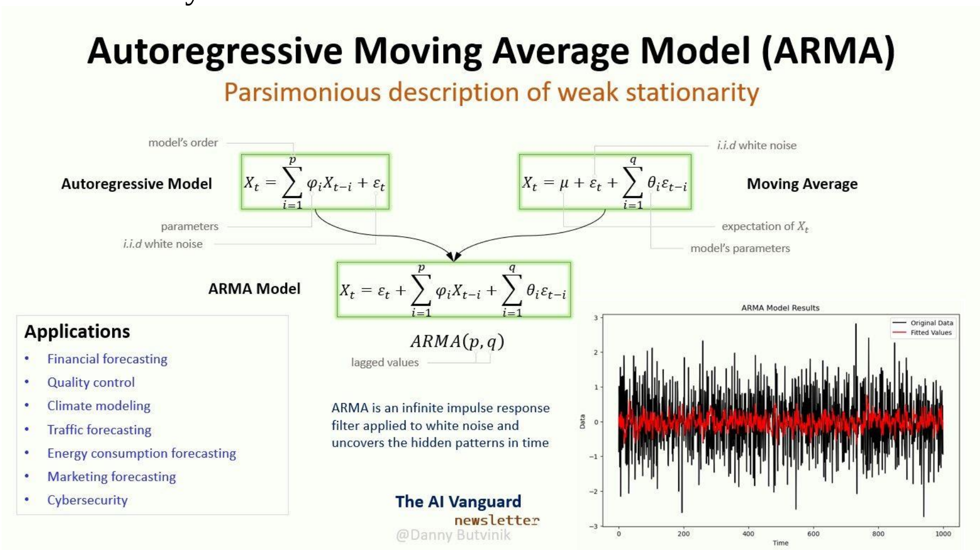
Assumption

The ARMA model assumes that the time series data is stationary. This lets the model capture and model the data's autocorrelation and partial autocorrelation patterns.

In practice, though, many time series data sets are not stationary and need to be changed or modeled in other ways to become stationary.

Box and *Jenkins* introduced the concept of differencing to address this ARMA model's limitation, which involves taking the difference between consecutive observations in the time series data to create a stationary time series.

The resulting model, the autoregressive integrated moving average (ARIMA) model, is an extension of the ARMA model that can handle non-stationary time series data.



To begin with, let’s establish a few fundamental principles. A time series yt is a variable consisting of observations that were recorded in equidistant periods of time. Regardless whether the units of time were the milliseconds, days, weeks, months or years, a forecasting method can be equally well applied to all of them. The

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time series must be cleared of any outliers and duplicate values with the same time-stamp, which is very important if we are engaged in some form of data mining. These sorts of data usually suffer from less attention from the casual user, so you should pay attention to cleaning up of your data first *Box - Jenkins Analysis* refers to a systematic method of identifying, fitting, checking, and using integrated autoregressive, moving average (ARIMA) time series models. The method is appropriate for time series of medium to long length (at least 50 observations).

In this chapter we will present an overview of the Box-Jenkins method, concentrating on the how-to parts rather than on the theory. Most of what is presented here is summarized from the landmark book on time series analysis written by George Box and Gwilym Jenkins (1976).

One type of model that does account for autocorrelation is the Autoregressive Integrated Moving Average (ARIMA) model, which is fit using a methodology developed by George Box and Gwilym Jenkins (1970). The application of ARIMA models in health sector is varied, however, it has been used extensively for (i) outbreak detection in the arena of infectious diseases and in (ii) the evaluation of population level health interventions in the format of interrupted time series analysis. Both of these methods require the formal characterization of the inherent pattern in a time series, and using this pattern to forecast future behavior of the time series. For outbreak detection, we forecast the 95% confidence interval for a time series, and deviation of the actual time series values from within 95% CI bounds would constitute a signal. In the interrupted time series, the time series is forecasted into the future, and deviations of actual values from the forecasted values is considered to be a causal effect of public health intervention.

Note:

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- ARIMA models do NOT predict rare “black swan” events, as there is no pattern in the time series to suggest a future event of this type.
- The causal framework for ARIMA model differs slightly from Epidemiology frame, and is more consistent with the Granger definition of a cause from economics.

Data Requirements

The data requirements to fit an ARIMA model are:

- A univariate time series (count or continuous) with at least 50-100 observations
- If the time series consists of count data, the interval over which the count is taken must remain the same over time
- If the time series consists of continuous data, the interval between measurements must remain the same over time
- Data must be presented in a vertical vector (column of data)

1. Literature Review

Components and Fitting of ARIMA Models

Overview:

The ARIMA model divides the pattern of a time series into three components: the autoregressive component, p, which describes how observations are related to each other as the result of being close together in time; the differencing component, d, which is used to make a time series stationary (see below); and the moving average component, q, which describes outside “shocks” to the system.

Stationarity Assumption:

A key requirement of ARIMA models is that the data set of interest is stationary, meaning that it has a constant mean and variance over time. If a data set is not stationary to begin with, stationarity can be achieved by a process called “differencing,” which is represented by the “d” component of the model.

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Model Identification:

Assuming for the moment that there is no seasonal variation, the objective of the model identification step is to select values of *d* and then *p* and *q* in the *ARIMA(p,d,q)* model. When the series exhibits a trend, we may either fit and remove a deterministic trend or difference the series. Box-Jenkins seem to prefer differencing, while several other authors prefer the deterministic trend removal.

The first step, in either case, is to look at the plots of the autocorrelations and partial autocorrelations. A series with a trend will have an autocorrelation patterns similar to the following:

By considering the patterns of the autocorrelations and the partial autocorrelations, we can guess a reasonable model for the data. The following chart shows the autocorrelation patterns that are produced by various types of ARMA models.

Model	**Autocorrelations**	**Partial Autocorrelations**
ARIMA(p,d,0)	Infinite. Tails off.	Finite. Cuts off after *p* lags.
ARIMA(0,d,q)	Finite. Cuts off after *q* lags.	Infinite. Tails off.
ARIMA(p,d,q)	Infinite. Tails off.	Infinite. Tails off.

The identification phase determines the values of *d* (differencing), *p* (autoregressive order), and *q* (moving average order). By studying the two autocorrelation plots, you estimate these values.

Differencing

The level of differencing is estimated by considering the autocorrelation plots. When the autocorrelations die out quickly, the appropriate value of *d* has been found.

Value of p The value of p is determined from the partial autocorrelations of the appropriately differenced series. If the partial autocorrelations cut off after a few lags, the last lag with a large value would be the estimated value of p. If the partial autocorrelations do

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not cut off, you either have a moving average model (p=0) or an ARIMA model with positive p and q.

Value of q

The value of *q* is found from the autocorrelations of the appropriately differenced series. If the autocorrelations cut off after a few lags, the last lag with a large value would be the estimated value of *q*. If the autocorrelations do not cut off, you either have an autoregressive model *(q=0)* or an ARIMA model with a positive *p* and *q*.

The identification steps involve fitting the autoregressive component (variable “p”), the moving average component of the ARIMA model (variable “q”), as well any required differing to make the time series stationary or to remove seasonal effects (variable “d”). Together, these user-specified parameters are called the order of ARIMA. The formal specification of the model will be ARIMA (p,d,q) when the model is reported.

The first step in model identification is to ensure the process is stationary. Stationarity can be checked with a Dickey-Fuller Test. Any non-significant value under model assumptions suggests the process is non-stationary. The process must be converted to a stationary process to proceed, and this is accomplished by the differencing the time series using a lag in the variable as well as removing any seasonality effects. The lagged values used to difference the time series will constitute the “d” order.

Ex. An additive difference of 1 and seasonal difference of 12 is reported as d=(1,12)

Once the process is stationary, we fit the autoregressive and moving average components. To fit the model we use the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) in addition to various model fitting tools provided by software. There are various sets of rules to guide p and q fitting in lower order processes, but generally we let the statistical software fit up to 12-14 orders for AR and MA, and suggest combinations that

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minimize an AIC or BIC criterion. This part is as much as an artform as it is a structured process. The goal during this phase is to minimize the AIC/BIC criterion.

Model Estimation and Diagnostic Checking

Maximum Likelihood Estimation

Once you have guesstimated values of *p, d,* and *q*, you are ready to estimate the phis and thetas. This program follows the maximum likelihood estimation process outlined in Box-Jenkins (1976). The maximum likelihood equation is solved by nonlinear function maximization. Backcasting is used to obtain estimates of the initial residuals. The estimation process is calculation intensive and iterative, so it often takes a few seconds to obtain a solution.

The estimation procedure involves using the model with p, d and q orders to fit the actual time series. We allow the software to fit the historical time series, while the user checks that there is no significant signal from the errors using an ACF for the error residuals, and that estimated parameters for the autoregressive or moving average components are significant.

Diagnostic Checking

Once a model has been fit, the final step is the diagnostic checking of the model. The checking is carried out by studying the autocorrelation plots of the residuals to see if further structure (large correlation values) can be found. If all the autocorrelations and partial autocorrelations are small, the model is considered adequate and forecasts are generated. If some of the autocorrelations are large, the values of *p* and/or *q* are adjusted and the model is re-estimated.

This process of checking the residuals and adjusting the values of *p* and *q* continues until the resulting residuals contain no additional structure. Once a suitable model is selected, the program may be used to generate forecasts and associated probability limits.

Forecasting:

After a model is assured to be stationary, and fitted such that there

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is no information in the residuals, we can proceed to forecasting. Forecasting assesses the performance of the model against real data. There is an option to split the time series into two parts, using the first part to fit the model and the second half to check model performance. Usually the utility of a specific model or the utility of several classes of models to fit actual data can be assessed by minimizing a value such as root mean square.

Arima models

ARIMA stands for Autoregressive Integrated Moving Average. It is a type of time series forecasting model that uses past data points to make predictions about future values. ARIMA models are used to analyze and forecast time series data such as sales, stock prices, and other economic indicators. ARIMA models are based on the assumption that the underlying process generating the data is stationary, meaning that the mean and variance of the data remain constant over time. The model uses three parameters to capture

The following data is needed to fit an ARIMA model:

• A countable or continuous univariate time series with at least 50–100 observations

In the event that the time series contains count data, If the time series is made up of continuous data, the interval between measurements must also remain constant across time. the interval during which the count is taken must remain the same.

• A vertical vector must be used to convey the data (column of data)

1.1 What is can be forecast?

Forecasting is the process of making predictions about the future based on past and present data. Forecasts can be made for a variety of topics, including weather, economic trends, stock market performance, consumer behavior, and political events.

Many different circumstances call for forecasting, including selecting whether to construct a new power plant in the next five years, arranging workers for a call center the following week, and stocking an inventory. Predictions may be necessary months or even

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years in advance (for capital projects), or even only a few minutes before (for telecommunication routing). Forecasting is a crucial tool for effective and efficient planning, regardless of the situations or time frames involved.

Predicting certain things is simpler than others. Next morning's sunrise timing can be predicted with accuracy. The lottery numbers for tomorrow, however, cannot be predicted with any degree of accuracy. The likelihood of an

1.2 forecasting, planning and gools setting

Forecasting is the process of making predictions about the future based on past and present data. Forecasting can be used to help businesses plan for the future by providing an estimate of future demand for products and services. Planning is the process of setting goals and objectives, and then developing strategies to achieve those goals. Planning helps businesses to identify potential risks and opportunities, and to develop strategies to take advantage of them. Goals setting is the process of defining what a business In business, forecasting is a common statistical task that aids in decision-making regarding the scheduling of production, transportation, and staff as well as serving as a roadmap for long-term strategic planning. Yet, corporate forecasting is typically performed ineffectively and is frequently mistaken for planning and objectives. They each represent a distinct entity.

Forecasting

Is about making the most accurate projections possible given all the information at our disposal, including past data and knowledge of any potential future events.

Your desired outcomes are your goals. Objectives and forecasts should be connected, but this doesn't always happen. Too often, objectives are established without a strategy for achieving them and without forecasts for whether they are realistic.

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Planning

- Is a reaction to projections and objectives. Planning entails choosing the best course of action to take in order to make your forecasts and goals align.
- Since forecasting can be useful in many aspects of a company, it should be a fundamental component of management's decision-making processes. Depending on the individual application, modern businesses need forecasts for the short term, medium term, and long term.
- For the scheduling of staff, manufacturing, and transportation, short-term projections are required. Forecasts of demand are frequently needed as part of the scheduling process.
- For the purpose of purchasing raw materials, hiring workers, or purchasing machinery and equipment, medium-term predictions are necessary to assess the future resource requirements.
- Strategic planning makes use of long-term projections. Market prospects, environmental factors, and other considerations must be taken into

1.3 determining what to forecast

When determining what to forecast, it is important to consider the purpose of the forecast. Different forecasting techniques are better suited for different types of data and different goals. For example, if the goal is to predict future sales, then a time series forecasting technique may be more appropriate than a regression analysis. Additionally, it is important to consider the availability of data and the accuracy of the forecast. If there is limited data available or if the forecast needs to be highly accurate, then more sophisticated forecasting techniques

Making decisions regarding what should be forecasted is necessary in the early phases of a forecasting endeavor. If predictions are necessary, for instance, for products in a manufacturing setting, it is vital

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determine whether forecasts are required for:

1. Is it for each product line or for categories of products?
2. For each and every sales outlet, for outlets categorized by region, or just for overall sales?
3. Are the data weekly, monthly, or yearly?

Moreover, the predicting horizon must be taken into account. Will forecasts be needed for the next month, the next six months, or the next 10 years? Several model types will be required, depending on which forecast horizon is most crucial.

How often are forecasts necessary? necessary forecasts

It is preferable to use an automated system than to use labor-intensive manual procedures for items that need to be produced regularly.

Before putting a lot of effort into creating the predictions, it is important to take the time to speak with the people who will use them to make sure you understand their needs and how the forecasts will be used.

Finding or gathering the data on which the forecasts will be based is then necessary after it has been determined what forecasts are necessary. It's possible that the forecasting data already exist. Nowadays, there are many data records, therefore the forecaster's responsibility is frequently to determine where and how the necessary data are stored. The information could consist of a company's sales records, the historical Purchasing power for a good or a region's unemployment rate. Before creating appropriate forecasting methods, a forecaster may spend a significant amount of time locating and gathering the available data.

1.4 forecasting data and method

Forecasting data is data that is used to predict future events or trends. This data can come from a variety of sources, including economic indicators, consumer surveys, and historical data. Forecasting methods are the techniques used to analyze and interpret the data in order to make predictions. Common forecasting methods

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include time series analysis, regression analysis, and Monte Carlo simulations.

The right forecasting techniques mostly depend on the data at hand.

Qualitative forecasting techniques must be employed if there are no data available or if the data that are available are not pertinent to the forecasts. There are well-developed organized procedures to obtaining accurate projections without using past data, thus these methods are not just educated guesswork. Chapter 4 discusses these techniques.

When both of the following conditions are met, quantitative forecasting can be used:

There is numerical data about the past that is available, and it is plausible to predict that some patterns from the past will persist into the future.

There are many different quantitative forecasting techniques, many of which were developed inside certain disciplines for particular objectives. Each approach has unique characteristics, accuracies, and expenses that should be taken into account while selecting a certain strategy.

Most quantitative prediction problems employ cross-sectional data or time series data, which are gathered at regular periods over time (collected at a single point in time). We focus on the time series domain in this book because we are interested in predicting future data.

1.5 time series forecasting

A time series is a set of values observed sequentially through time. The series may be denoted by $XX1$, $XX2$, $\cdots$, $XXtt$, where t refers to the time period and X refers to the value. If the X's are exactly determined by a mathematical formula, the series is said to be *deterministic*. If future values can be described only by their probability distribution, the series is said to be a *statistical* or *stochastic* process.

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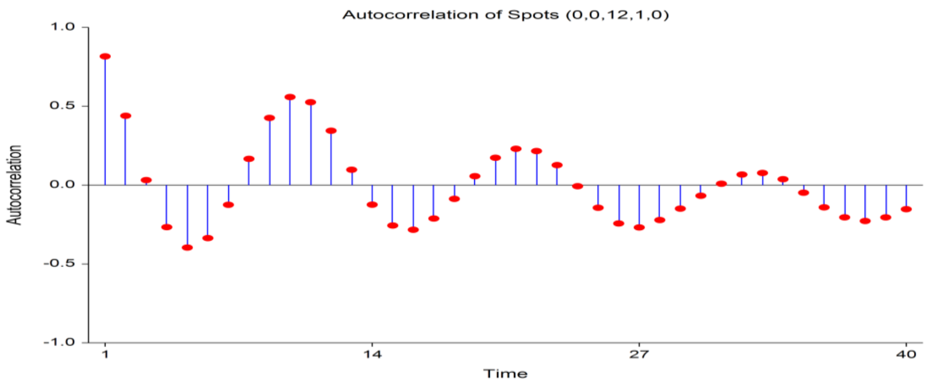
A special class of stochastic processes is a *stationary stochastic process*. A statistical process is stationary if the probability distribution is the same for all starting values of *t*. This implies that the mean and variance are constant for all values of *t*. A series that exhibits a simple trend is not stationary because the values of the series depend on *t*. A stationary stochastic process is completely defined by its mean, variance, and autocorrelation function. One of the steps in the Box - Jenkins method is to transform a non-stationary series into a stationary one.

Autocorrelation Function

The stationary assumption allows us to make simple statements about the correlation between two successive values, $XXtt$ and $XXtt+kk$. This correlation is called the *autocorrelation of lag k* of the series. The autocorrelation function displays the autocorrelation on the vertical axis for successive values of k on the horizontal axis. The following figure shows the autocorrelation function of the sunspot data.



Time series forecasting is the process of using historical data to predict future values of a time series. It is a type of predictive analytics that uses time-series data to forecast future trends and patterns. Time series forecasting can be used in a variety of applications, such as predicting stock prices, sales, and customer

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demand. It can also be used to forecast weather patterns, economic trends, and other types of data. Time series forecasting is an important tool for businesses to make informed decisions about the future.

A statistical technique called time series analysis is used to examine and model the trends and patterns in a collection of data points that have been gathered over time. It is frequently used to analyze data trends and forecast future outcomes in disciplines including economics, finance, and environmental science.

In time series analysis, a number of approaches are utilized, such as:

Decomposition: This entails dissecting the time series into such as trend, seasonality, and residuals, which are its constituent pie ces.

To better visualize trends and patterns, smoothing includes em ploying mathematical techniques to remove irregularities from time s eries data.

To forecast future events, ARIMA modeling requires fitting a n autoregressive integrated moving average (ARIMA) model to time series data.

A prominent technique for predicting future values in a time s eries by utilizing a weighted average of previous observations is exp onential smoothing.

The Fourier analysis includes converting a time series into the frequency domain in order to pinpoint the frequencies of various dat a components.

Although time series analysis is an effective technique for ide ntifying trends in data and making predictions, it can also be difficult and complex.

It's crucial to A method should be carefully chosen, and the conclusions should be interpreted in light of the chosen approach's constraints and underlying assumptions.

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Yes, that is true! Time series analysis is an effective tool, but in order to properly interpret the results, it's also critical to comprehend the assumptions and constraints of each technique. Making ensuring that the data being studied is stationary—that is, that its mean and variance remain consistent throughout time—is also crucial. Using methods like differences or transformations, such the log transformation, it is possible to make non-stationary data stationary.

Checking for outliers or abnormalities in the data is a crucial part of time series analysis because they can significantly affect the outcomes. Statistical methods like the Z-score or the median absolute deviation can be used to identify outliers.

In conclusion, time series analysis is a useful technique for identifying trends in data over time, but it's also crucial to be aware of its constraints and underlying presuppositions, as well as to pre-process the data before beginning the analysis.

Time series data examples include: daily IBM stock prices; monthly rainfall; quarterly Amazon sales; and annual Google profits. A time series is anything that has been observed progressively over time. Only time series that are observed at regular periods of time will be taken into consideration (e.g., hourly, daily, weekly, monthly, quarterly, annually). Time series with irregular spacing can also happen.

Forecasting time series data requires: The goal is to predict how the observations will proceed in the future. Figure 1.1 depicts Australian beer production on a quarterly basis from 1992 to the second quarter of 2010.

Forecasts for the following two years are shown by the blue lines. See how the seasonal pattern shown in the historical data has been duplicated for the following two years by the projections. The 80% prediction ranges are displayed in the dark colored area. This means that there is an 80% chance that each future number will be found in the region of darkness. 95% prediction intervals are

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displayed in the area that is lightly shaded. These prediction intervals are a practical tool for showing forecast uncertainty. Because it is anticipated that the projections will be correct in this situation, the prediction intervals are fairly small.

The most basic time series forecasting techniques don't try to identify the variables that influence a variable's behavior; instead, they just use data on the variable to be forecast. As a result, they will extrapolate trends and seasonal patterns while ignoring all other data, including marketing campaigns, competition activity, changes in economic conditions, and so forth. Decomposition models, exponential smoothing methods, and ARIMA models are some of the time series models used for forecasting.

Forecasting using time series and predictor variables

In time series forecasting, predictor variables are frequently beneficial. For instance, let's say we want to predict the summertime hourly electricity demand (ED) for a hot region. An example of a model with predictor variables is ED=f (current temperature, strength of economy, population, time of day, day of week, error). ED=f(current temperature, strength of economy, population, time of day, day of week, error) (current temperature, strength of economy, population, time of day, day of week, error). There will always be variations in electricity demand that cannot be explained by the predictor variables, therefore the relationship is not accurate. The "error" term on the right accounts for chance variations and the impacts of pertinent factors that are not taken into account by the model. Because it explains what, we refer to this as an explanatory model.

Time Series and Stochastic Processes

Time Series. A time series is a set of observations generated sequentially over time.

If the set is continuous, the time series is said to be *continuous*. If the set is discrete, the time series is said to be *discrete*. Thus, the observations from a discrete time series made at times $\tau 1$, $\tau 2$,…,

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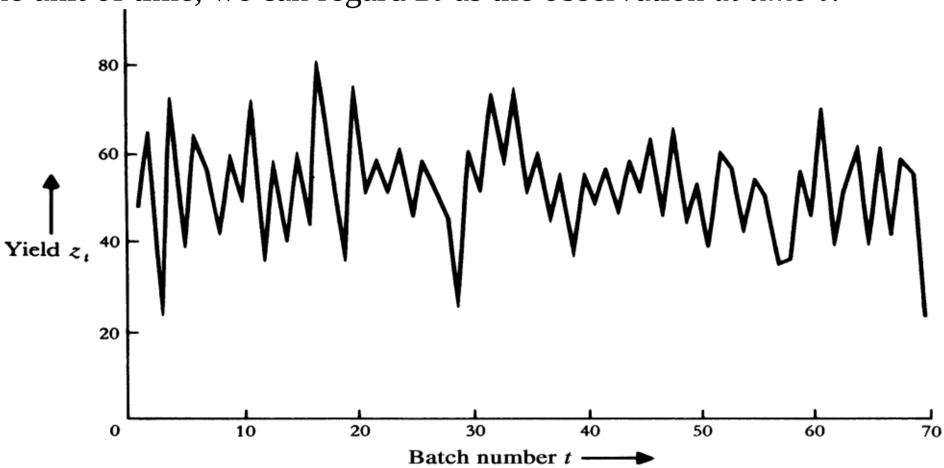
$\tau t, \ldots, \tau N$ may be denoted by $z(\tau 1)$, $z(\tau 2), \ldots, z(\tau t), \ldots, z(\tau N)$. In this book, we consider only discrete time series where observations are made at a fixed interval h. When we have N *successive* values of such a series available for analysis, we write $z1, z2, \ldots, zt, \ldots, zN$ to denote observations made at equidistant time intervals $\tau 0 + h$, $\tau 0 + 2h, \ldots, \tau 0 + th, \ldots, \tau 0 + Nh$. For many purposes, the values of $\tau 0$ and h are unimportant, but if the observation times need to be defined exactly, these two values can be specified. If we adopt $\tau 0$ as the origin and h as the unit of time, we can regard zt as the observation *at time t*.



Discrete time series may arise in two ways:

1. By *sampling* a continuous time series: For example, in the situation shown in Figure 1.2, where the continuous input and output from a gas furnace was sampled at intervals of 9 seconds.

2. By *accumulating* a variable over a period of time: Examples are rainfall, which is usually accumulated over a period such as a day or a month, and the yield from a batch process, which is accumulated over the batch time. For example, Figure 2.1 shows a time series consisting of the yields from 70 consecutive batches of a chemical process. The series shown here is included as Series F in Part Five of this book.

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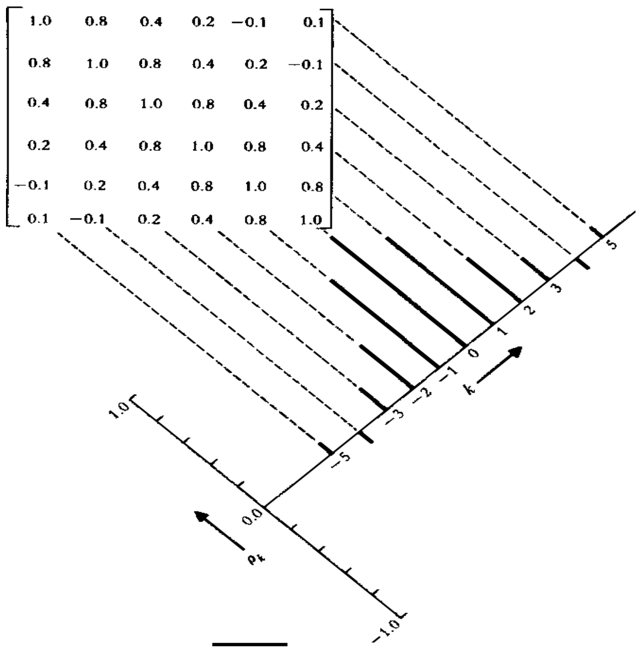
Autocovariance and Autocorrelation Functions

It was seen in Section 2.1.2 that the autocovariance coefficient γ_k, at lag k, measures the covariance between two values z_t and z_{t+k} a distance k apart. The plot of γ_k versus lag k is called the *autocovariance function* $\{\gamma_k\}$ of the stochastic process. Similarly, the plot of the autocorrelation coefficient ρ_k as a function of the lag k is called the *autocorrelation function* $\{\rho_k\}$ of the process. Note that the autocorrelation function is dimensionless, that is, independent of the scale of measurement of the time series. Since $\gamma_k = \rho_k\sigma^2_z$, knowledge of the autocorrelation function $\{\rho_k\}$ and the variance σ^2_z is equivalent to knowledge of the autocovariance function $\{\gamma_k\}$.

The autocorrelation function, shown in Figure 2.5 as a plot of the diagonals of the autocorrelation matrix, reveals how the correlation between any two values of the series changes as their separation changes. Since $\rho_k = \rho_{-k}$, the autocorrelation function is

FIGURE



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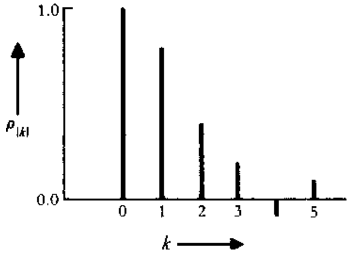
AUTOCORRELATION FUNCTION AND SPECTRUM OF STATIONARY PROCESSES



Positive half of the autocorrelation function

Estimation of Autocovariance and Autocorrelation Functions

Up to now, we have only considered the theoretical autocorrelation function that describes a
stochastic process. In practice, we have a finite time series z_1, z_2,…, z_N of N observations, from which we can only obtain *estimates* of the mean μ and the autocorrelations. The mean μ = [z_t] is estimated as in (2.1.3) by the sample mean **Standard Errors of Autocorrelation Estimates**

To identify a model for a time series, using methods to be described in Chapter 6, it is useful to have a rough check on whether ρ_k is effectively zero beyond a certain lag. For this purpose, we can use the following expression for the approximate variance of the estimated autocorrelation coefficient of a stationary normal process given by Bartlett (1946):

AUTOCORRELATION FUNCTION AND SPECTRUM OF STATIONARY PROCESSES

Autoregressive and Moving Average Processes

The representations (3.1.1) and (3.1.4) of the general linear process would not be very useful in practice if they contained an infinite number of parameters ψ_j and π . We now describe a way to introduce parsimony and arrive at models that are representationally useful for practical applications.

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Autoregressive Processes. Consider first the special case of (3.1.4) in which only the first

p of the weights are nonzero. The model may be written as

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \phi_2 \tilde{z}_{t-2} + \cdots + \phi_p \tilde{z}_{t-p} + a_t$$

AUTOREGRESSIVE PROCESSES

Stationarity Conditions for Autoregressive Processes

The parameters $\phi_1, \phi_2, \ldots, \phi_p$ of an AR(p) process

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \cdots + \phi_p \tilde{z}_{t-p} + a_t$$

Second-Order Autoregressive Process

Stationarity Condition. The second-order autoregressive process can be written as

$$\tilde{z}_t = \phi_1 \tilde{z}_{t-1} + \phi_2 \tilde{z}_{t-2} + a_t$$

Partial Autocorrelation Function

In practice, we typically do not know the order of the autoregressive process initially, and the order has to be specified from the data. The problem is analogous to deciding on the number of independent variables to be included in a multiple regression. The partial autocorrelation function is a tool that exploits the fact that, whereas an AR(p) process has an autocorrelation function that is infinite in extent, the partial autocorrelations are zero beyond lag p.

The partial autocorrelations can be described in terms of p nonzero *functions* of the autocorrelations. Denote by ϕ_{kj} the jth coefficient in an autoregressive representation of order k, so that ϕ_{kk} is the last coefficient. From (3.2.4), the ϕ_{kj} satisfy the set of equations

$$\rho_j = \phi_{k1}\rho_{j-1} + \cdots + \phi_{k(k-1)}\rho_{j-k+1} + \phi_{kk}\rho_{j-k} \quad j = 1, 2, \ldots, k$$

Estimation of the Partial Autocorrelation Function

The partial autocorrelations may be estimated by fitting successively autoregressive models of orders 1, 2, 3,… by least squares and picking out the estimates $\hat{\phi}_{11}, \hat{\phi}_{22}, \hat{\phi}_{33}, \ldots$ of the last coefficient fitted at each stage. Alternatively, if the values of the parameters are not too close to the nonstationary boundaries, approximate Yule--Walker estimates of the successive autoregressive

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models may be employed. The estimated partial autocorrelations can then be obtained by substituting estimates r_j for the theoretical autocorrelations in (3.2.30), to yield

$r_j = \hat{\phi}_{k1} r_{j-1} + \hat{\phi}_{k2} r_{j-2} + \cdots + \hat{\phi}_{(k-1)} r_{j-k+1} + \hat{\phi}_{kk} r_{j-k} \quad j = 1, 2, \ldots, k$

Standard Errors of Partial Autocorrelation Estimates

It was shown by Quenouille (1949) that on the hypothesis that the process is autoregressive of order p, the estimated partial autocorrelations of order $p + 1$, and higher, are approximately independently and normally distributed with zero mean. Also, if n is the number of observations used in fitting,

$\text{var}[\hat{\phi}_{kk}] \simeq 1/n \ , \ k \geq p + 1$

MOVING AVERAGE PROCESSES

Invertibility Conditions for Moving Average Processes

We now derive the conditions that the parameters $\theta_1, \theta_2, \ldots, \theta_q$ must satisfy to ensure the
invertibility of the MA(q) process:

$\tilde{z}_t = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} = (1 - \theta_1 B - \cdots - \theta_q B^q) a_t = \theta(B) a_t$

Moving Average Parameters in Terms of Autocorrelations. If $\rho_1, \rho_2, \ldots, \rho_q$ are known,
the q equations (3.3.4) may be solved for the parameters $\theta_1, \theta_2, \ldots, \theta_q$. However, unlike
the Yule--Walker equations (3.2.6) for an autoregressive process, the equations (3.3.4)
are nonlinear. Hence, except in the simple case where $q = 1$, which is discussed shortly,
these equations have to be solved iteratively. Estimates of the moving average parameters
may be obtained by substituting estimates r_k for ρ_k and solving the resulting equations.
However, unlike the autoregressive estimates obtained from the Yule--Walker equations

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the resulting moving average estimates may not have high statistical efficiency. Nevertheless, they can provide useful rough estimates at the model identification stage discussed in Chapter 6. Furthermore, they provide useful starting values for an iterative parameter estimation procedure, discussed in Chapter 7, which converges to the efficient maximum likelihood estimates.

Spectrum. For the MA(q) process,

$(B) = \theta(B) = 1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

First-Order Moving Average Process

We have already **introduced** the MA(1) process

$\tilde{z}_t = a_t - \theta_1 a_{t-1} = (1-\theta_1 B) a_t$

and we have seen that θ_1 must lie in the range $-1 < \theta_1 < 1$ for the process to be invertible.

The process is, of course, stationary for all values of θ_1.

Autocorrelation Function. It is easy to see that the variance of this process equals

$\gamma_0 = (1+\theta_1^2)\sigma_a^2$

The autocorrelation function is $\rho_k = \begin{cases} \frac{-\theta_1}{1+\theta_1^2} & k = 1 \\ 0 & k > 1 \end{cases}$ from which it is noted that ρ_1 must satisfy $|\rho_1| = |\theta_1|/(1+\theta_1^2) \leq \frac{1}{2}$. Also, for $k = 1$, we find that $\rho_1\theta_1^2 + \theta_1 + 1$ 0 with roots for θ_1 equal to $\theta_1 = (-1\pm\sqrt{1-4\rho_1^2})/(2\rho_1)$. Since the product of the roots is unity, we see that if θ_1 is a solution, so is θ_1^{-1}. Furthermore, if θ_1 satisfies the invertibility condition $|\theta_1| < 1$, the other root θ_1^{-1} will be greater than unity and will not satisfy the condition. For example, if $\rho_1 = -0.4$, the two solutions are $\theta_1 = 0.5$ and $\theta_1 = 2.0$.However, only the solution $\theta_1 = 0.5$ corresponds to an invertible model.

Second-Order Moving Average Process

Invertibility Conditions. The second-order moving average process is defined by

$\tilde{z}_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} = (1-\theta_1 B - \theta_2 B^2) a_t$

and is stationary for all values of θ_1 and θ_2. However, it is invertible only if the roots of the characteristic equation $1 - \theta_1 B - \theta_2 B^2 = 0$

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Partial Autocorrelation Function. The exact expression for the partial autocorrelation function of an MA(2) process is complicated, but it is dominated by the sum of two exponentials if the roots of the characteristic equation $1 - \theta 1B - \theta 2B2 = 0$ are real, and by a damped sine wave if the roots are complex. Thus, it behaves like the autocorrelation function of an AR(2) process. The autocorrelation functions and partial autocorrelation functions for various values of the parameters within the invertible region are shown in Figure 3.7. Comparison of Figure 3.7 with Figure 3.2, which shows the corresponding

1.6 A the basic steps in forecasting

1. Define the forecasting problem: Identify the purpose of the forecast, the time frame, and the data that will be used.
2. Select a forecasting method: Choose a forecasting technique that best fits the problem.
3. Collect data: Gather historical data relevant to the problem.
4. Analyze data: Examine the data to identify trends, seasonality, and other patterns.
5. Develop a forecast: Use the chosen forecasting method to generate a forecast.
6. Evaluate the forecast: Compare the forecast to actual results and assess its accuracy.
7. Implement and monitor the forecast: Put the forecast into action and track its performance over time.

1.7 the statistical forecasting perspective

Statistical forecasting is a method of predicting future events or trends based on past data. It involves the use of mathematical models and algorithms to analyze historical data and make predictions about future outcomes. Statistical forecasting can be used to predict a variety of outcomes, including sales, customer demand, economic trends, and more. Statistical forecasting is often used in business and economics to help make decisions about investments, production levels, and other important decisions.

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1.8 BOX JENKINS MODEL

The Box-Jenkins method refers to the iterative application of the following three steps:

1. ***Identification***. Using plots of the data, autocorrelations, partial autocorrelations, and other information, a class of simple ARIMA models is selected. This amounts to estimating appropriate values for *p*, *d*, and *q*.
2. ***Estimation***. The phis and thetas of the selected model are estimated using maximum likelihood techniques, back casting, etc., as outlined in Box-Jenkins (1976).
3. ***Diagnostic Checking***. The fitted model is checked for inadequacies by considering the autocorrelations of the residual series (the series of residual, or error, values).

These steps are applied iteratively until step three does not produce any improvement in the model. We will now go over these steps in detail.

The Jenkins model is a software development model that is based on the principles of continuous integration and continuous delivery. It is an open-source automation server that can be used to automate the building, testing, and deployment of software applications. The model is based on the idea that software should be developed in small increments, with each increment tested and deployed quickly. This allows for faster feedback and more frequent releases. The model also encourages collaboration between developers, testers, and operations teams to ensure that the software is of high quality and meets customer requirements.

Fundamentals To anticipate or predict future value over a period of time (for example, stock price) is to use simple language. There are various methods for predicting the value; for instance, let's take the case of a firm XYZ that tracks website traffic hourly and wishes to anticipate how much traffic would be there in the upcoming hour.

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What method will you use to predict the traffic for the future hour, may I ask?

Finding the average of all observations, taking the mean of the most recent two observations, giving more weight to the current observation and less to the past, or using interpolation are just a few examples of how different perspectives can differ. There are various techniques for predicting the values.

when Predicting time series values, 3 crucial terms need to be taken care of and the major goal of time series forecasting is to forecast these three terms.

The main task of time series forecasting is to forecast these three terms:

1) Seasonality

Seasonality is a simple term that means while predicting a time series data there are some months in a particular domain where the output value is at a peak as compared to other months. for example if you observe the data of tours and travels companies of past 3 years then you can see that in November and December the distribution will be very high due to holiday season and festival season. So while forecasting time series data we need to capture this seasonality.

2) Trend

The trend is also one of the important factors which describe that there is certainly increasing or decreasing trend time series, which actually means the value of organization or sales over a period of time and seasonality is increasing or decreasing.

3) Unexpected Events

Unexpected events mean some dynamic changes occur in an organization, or in the market which cannot be captured. for example a current pandemic we are suffering from, and if you observe the

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Sensex or nifty chart there is a huge decrease in stock price which is an unexpected event that occurs in the surrounding.

1.9. Model Type. The following options are available:

- All models. The Expert Modeler considers both ARIMA and exponential smoothing models.
- Exponential smoothing models only. The Expert Modeler only considers exponential smoothing models.
- ARIMA models only. The Expert Modeler only considers ARIMA models.

Expert Modeler considers seasonal models. This option is only enabled if a periodicity has been defined for the active dataset. When this option is selected, the Expert Modeler considers both seasonal and nonseasonal models. If this option is not selected, the Expert Modeler only considers nonseasonal models.

Events and Interventions. Enables you to designate certain input fields as event or intervention fields. Doing so identifies a field as containing time series data affected by events (predictable recurring situations, for example, sales promotions) or interventions (one-time incidents, for example, power outage or employee strike). The Expert Modeler does not consider arbitrary transfer functions for inputs identified as event or intervention fields.

Input fields must have a measurement level of Flag, Nominal, or Ordinal and must be numeric (for example, 1/0, not True/False, for a flag field), before they will be included in this list.

Outliers

Detect outliers automatically. By default, automatic detection of outliers is not performed. Select this option to perform automatic detection of outliers, then select the desired outlier types. See the topic Handling Outliers for more information.

Streaming TS Model Options

Handling Outliers

Univariate Series (TSMODEL algorithms)

Users can let the Expert Modeler select a model for them from:

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- All models (default).
- Exponential smoothing models only.
- ARIMA models only.

2.2 Gross Domestic Product (GDP) :

Gross Domestic Product (GDP) is the total monetary or market value of all the finished goods and services produced within a country's borders in a specific time period. As a broad measure of overall domestic production, it functions as a comprehensive scorecard of the country’s economic health.

(GDP) is one of the most well-known markers used to follow the soundness of a country's economy. It incorporates various factors, for example, consumption and venture. It's additionally a key factor in utilizing the Taylor rule. In this short article, we take a gander at why GDP is such a significant monetary factor, and what it implies for the two business analysts and financial specialists.

The Basics of GDP

GDP includes all private and public consumption, government outlays, investments, additions to private inventories, paid-in construction costs, and the foreign balance of trade (exports are added, imports are subtracted).

It speaks to the absolute dollar estimation all things considered and benefits created over a particular timespan, frequently alluded to as the size of the economy. Gross domestic product is generally communicated as a correlation with the past quarter or year.

KEY TAKEAWAYS

- Gross residential item tracks the strength of a nation's economy.
- It speaks to the estimation everything being equal and administrations created over a particular timeframe inside a nation's fringes.
- Economists can utilize GDP to decide if an economy is developing or encountering a downturn.
- Investors can utilize GDP to settle on ventures choices—a terrible economy implies lower profit and lower stock costs.

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Total national output (GDP) Defined

Gross domestic product is essentially used to check the soundness of a nation's economy. It is the money related estimation of all the completed merchandise and enterprises created inside a nation's outskirts in a particular timeframe and incorporates anything delivered by the nation's residents and outsiders inside its fringes.

As per the International Monetary Fund, the United States is the world's biggest economy, trailed by China and Japan.

Total national output is the absolute benefit of everything created in the nation. It doesn't make a difference if it's delivered by residents or outsiders. On the off chance that they are situated inside the nation's limits, their creation is remembered for GDP.

To evade twofold checking, GDP incorporates the last estimation of the item, yet not the parts that go into it. For instance, a U.S. footwear maker utilizes bands and different materials made in the United States. Just the estimation of the shoe gets checked; the shoelace doesn't.

In the United States, the Bureau of Economic Analysis estimates GDP quarterly. Every month, it reexamines the quarterly gauge as it gets refreshed information.

Calculating GDP

The components of GDP include personal consumption expenditures plus business investment plus government spending plus (exports minus imports). Now that you know what the components are, it's easy to calculate a country's gross domestic product using this standard formula: C + I + G + (X - M).

When economists talk about the “size” of an economy, they are referring to GDP.

Types

There are many different ways to measure a country's GDP. It's important to know all the different types and how they are used.

Genuine GDP: To look at GDP by year, the BEA expels the impacts of expansion. Else, it may appear as though the economy is

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developing when actually it's experiencing twofold digit swelling. The BEA computes genuine GDP by utilizing a value deflator. It reveals to you how much costs have changed since a base year. The BEA increases the deflator by the ostensible GDP. The BEA makes the accompanying three significant differentiations:

Development Rate: The GDP development rate is the rate increment in GDP from quarter to quarter. It lets you know precisely whether the economy is becoming speedier or more slow than the quarter previously. Most nations utilize genuine GDP to expel the impact of expansion. If the economy produces less than the quarter before, it contracts and the growth rate is negative. This signals a recession. If it stays negative long enough, the recession turns into a depression.

How GDP Affects You

Gross domestic product impacts individual fund, speculations, and employment development. Speculators take a gander at a countries' development rate to choose in the event that they ought to alter their advantage distribution. They likewise contrast nation development rates with locate their best worldwide chances. They buy portions of organizations that are in quickly developing nations.

The U.S. national bank, the Federal Reserve, utilizes the development rate to decide fiscal arrangement. It executes expansionary money related strategy to avert downturn and contractionary financial approach to avoid swelling. Its essential instrument is the government finances rate.

For instance, on the off chance that the development rate is expanding, at that point the Fed raises financing costs to stem expansion. For this situation, you should secure a fixed-rate contract. Your installments on a movable rate home loan will ascend alongside the fed finances rate.

In the event that development eases back or gets negative, at that point you should refresh your resume. Slow monetary development prompts cutbacks and joblessness. That can take a while.

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It requires some investment for administrators to gather the cutback list and get ready leave bundles.

Utilize the GDP report from the BEA to figure out which divisions of the economy are developing and which are declining.

You can go after positions in developing segments. In any event, during the 2008 money related emergency, human services ventures kept on including employments. This report additionally encourages you decide if you ought to put resources into, state, a tech-explicit shared reserve versus a store that spotlights on agribusiness.

Investment:-

A speculation is an advantage or thing procured with the objective of creating pay or appreciation. In a financial sense, a speculation is the acquisition of merchandise that are not devoured today however are utilized later on to make riches. In account, a venture is a money related resource obtained with the possibility that the benefit will give salary later on or will later be sold at a more significant expense for a benefit.

A speculation consistently concerns the cost of some advantage today (time, cash, exertion, and so forth.) with expectations of a more noteworthy result later on than what was initially placed in.

Contributing is giving cash something to do to begin or extend an undertaking - or to buy an advantage or premium - where those assets are then given something to do, with the objective to pay and expanded an incentive after some time. The expression "speculation" can allude to any component utilized for producing future pay. In the budgetary sense, this incorporates the acquisition of securities, stocks or land property among a few others. Furthermore, a built structure or other office used to deliver products can be viewed as a venture. The generation of products required to deliver different merchandise may likewise be viewed as contributing.

Making a move with expectations of raising future income can likewise be viewed as a speculation. For instance, when deciding to seek after extra training, the objective is regularly to expand

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information and improve aptitudes with expectations of eventually creating more salary. Since contributing is arranged toward future development or pay, there is hazard related with the interest for the situation that it doesn't work out or misses the mark. For example, putting resources into an organization that winds up failing or a task that comes up short. This is the thing that isolates contributing from sparing - setting aside is aggregating cash for sometime later that isn't in danger, while speculation is giving cash something to do for future increase and involves some hazard.

Financial development can be empowered using sound speculations at the business level. At the point when an organization builds or secures another bit of creation hardware so as to raise the all out yield of merchandise inside the office, the expanded generation can cause the country's (GDP) to rise. This enables the economy to develop through expanded generation dependent on the past hardware venture.

The IS-LM model, which means "speculation reserve funds" (IS) and "liquidity inclination cash supply" (LM) is a Keynesian macroeconomic model that shows how increments in venture at a national level mean increments in financial interest, and the other way around.

A speculation bank gives an assortment of administrations intended to help an individual or business in expanding related riches. This does exclude conventional purchaser banking. Rather, the organization centers around venture vehicles, for example, exchanging and resource the executives. Financing alternatives may likewise be accommodated the reason for helping with the these administrations.

Venture banking is a particular division of banking identified with the production of capital for different organizations, governments and different substances. Speculation banks guarantee new obligation and value protections for a wide range of enterprises, help in the closeout of protections, and help to encourage mergers and acquisitions, redesigns and merchant exchanges for the two foundations and private

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speculators. Venture banks likewise give direction to guarantors in regards to the issue and arrangement of stock, for example, with an IPO or rights advertising.

Saving:

Reserve funds, as indicated by Keynesian financial aspects, are what an individual has left over when the expense of their customer consumption is subtracted from the measure of discretionary cash flow earned in a given timeframe. For the individuals who are monetarily reasonable, the measure of cash left over after close to home costs have been met can be certain; for the individuals who will in general depend using a loan and credits to make a decent living, there is no cash left for investment funds. Reserve funds can be utilized to build pay through putting resources into various venture vehicles.

Saving account pays enthusiasm on money not required for day by day costs however accessible for a crisis. Stores and withdrawals are made by telephone, mail or at a bank office or ATM. Loan costs are higher than on financial records.

A currency advertise account requires a higher least equalization, pays more enthusiasm than other financial balances and permits barely any month to month withdrawals through registration benefits or charge card use.

A testament of store (CD) limits access to money for a specific period in return of a higher loan fee. Store terms go from a quarter of a year to five years; the more drawn out the term, the higher the loan cost. Compact discs have early-withdrawal punishments that can delete premium earned, so it is ideal to keep the cash in the CD for the whole term. (For related perusing, see "The amount Cash Should I Keep in the Bank?")

Consumption:

Consumption, in financial matters, the consumption of products and ventures by family units. Consumption is unmistakable from consumption use, which is the acquisition of merchandise and

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enterprises for use by families. Consumption contrasts from consumption use basically in light of the fact that strong merchandise, for example, cars, produce a use chiefly in the period when they are obtained, however they create "consumption administrations"

The investigation of consumption conduct assumes a focal job in both macroeconomics and microeconomics. Macroeconomists are keen on total consumption for two particular reasons. In the first place, total consumption decides total sparing, on the grounds that sparing is characterized as the bit of salary that isn't expended. Since total sparing feeds through the monetary framework to make the national inventory of capital, it pursues that total consumption and sparing conduct impacts an economy's long haul gainful limit. Second, since consumption use represents the majority of national yield, understanding the elements of total consumption use is fundamental to understanding macroeconomic vacillations and the business cycle.

Microeconomists have read utilization conduct for some, various reasons, utilizing consumption information to gauge destitution, to look at families' readiness for retirement, or to test hypotheses of rivalry in retail businesses. A rich assortment of family unit level information sources, (for example, the Consumer Expenditure Survey directed by the U.S. government) enables market analysts to analyze family spending conduct in minute detail, and microeconomists have additionally used these information to look at collaborations among consumption and other microeconomic conduct, for example, work chasing or instructive achievement.

In their investigations of consumption, business analysts for the most part draw upon a typical hypothetical system by accepting that purchasers base their uses on a balanced and educated appraisal regarding their present and future monetary conditions. This "levelheaded advancement" supposition that is untestable, nonetheless, without extra presumptions concerning why and how buyers care about their degree of consumption; along these lines purchasers' inclinations are thought to be caught by an utility capacity.

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For instance, business analysts generally expect (1) that the desperation of consumption needs will decay as the degree of consumption builds (this is known as a declining minimal utility of consumption), (2) that individuals like to confront less instead of more hazard in their consumption (individuals are chance opposed), and (3) that unavoidable vulnerability in future salary creates some level of prudent sparing. In light of a legitimate concern for straightforwardness, the standard renditions of these models likewise make some less-harmless presumptions, including affirmations that the delight yielded by the present consumption doesn't rely on one's past consumption (there are no propensities from an earlier time that impact the present consumption) and that present joy doesn't rely on correlation of one's consumption to the consumption of others (there is no "envy").

Inside the normal advancement system, there are two fundamental methodologies. The "life-cycle" model, first enunciated in "Utility Analysis and the Consumption Function" (1954) by financial experts Franco Modigliani and Richard Brumberg, recommends that families' spending choices are driven by family unit individuals' appraisals of use needs and salary over the rest of their lives, considering unsurprising occasions, for example, a sharp drop in pay at retirement. The standard adaptation of the life-cycle model likewise accept that customers would like to spend everything before they bite the dust (i.e., it expect there is no inheritance thought process). Life-cycle models are most normally utilized by microeconomists modeling household-level data on consumption, income, or wealth

Macroeconomists will in general utilize a disentangled variant of the advancement structure called the "perpetual salary speculation," whose sources follow back to market analyst Milton Friedman's treatise A Theory of the Consumption Function (1957). The changeless pay speculation overlooks the point by point treatment of socioeconomics and retirement enveloped in the life-cycle model,

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concentrating rather on the angles that issue most for macroeconomic examination, for example, expectations about the idea of the utilization work, which relates customer spending to components, as income, wealth, interest rates, and the like.

Friedman stated that by and large just around 33% of any bonus (a one-time unexpected increase) would be gone through inside a year. He further contended that a one-for-one relationship between's expanded salary and expanded spending would happen just when the pay increment was seen to mirror a perpetual change in conditions (e.g., another, more lucrative occupation).

The cutting edge numerical variants of the life-cycle and changeless salary theory models utilized by most financial experts carry some conceivable refinements to the first thoughts. For instance, the cutting edge models suggest that the negligible affinity to expend out of fortunes is a lot higher for poor than for rich families. This propensity makes it difficult to decide the effect of a tax break or government program on utilization spending without knowing whether it is pointed principally at low-riches or high-riches families. The hypothesis further shows that tax reductions or spending programs, (for example, expanded joblessness benefits) pointed principally at lower-pay families ought to be significantly increasingly compelling at invigorating or keeping up total spending than programs went for more extravagant family units.

3. Case Study

3.1 Data and Methodology

The data of the study obtained from According to official data from the ksa Monetary Agency, consists of annual data (GDP). We use ARIMA model for forecast one period a head of the series by applying Box-Jenkins approach. An ARIMA is a generalization of an ARIMA model. The model is generally referred to as ARIMA (p, d, q) model, where p, d and q are integers greater than or equal zero and

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refer to the order of autoregressive integrated and moving average aspects.

The Box-ARIMA model is a combination of the AR (Autoregressive) and MA (moving average) model as follows:

$Yt = \beta 0+ \beta 1Yt-1 +\ldots+ \beta pYt-p - \alpha 1Ut-1 -\alpha 2Ut-2 -\ldots- \alpha qUt-q + Ut$

The Box-Jenkins methodology is a five step process for identifying, selective and Assessing conditional means models.

3.2 Data Analysisi

Model Description

			Model Type
Model ID	والمطاعم والتجزئة الجملة تجارة والفنادق	Model_1	ARIMA(2,1,0)

The model description table contains an entry for each estimated model and includes both a model identifier and the model type. The model identifier consists of the name (or label) of the associated dependent variable and a system-assigned name. In the current example, the dependent variable is Sales of Men's Clothing and the system-assigned name is Model_1.

The Time Series Modeler supports both exponential smoothing and ARIMA models. Exponential smoothing model types are listed by their commonly used names such as Holt and Winters' Additive. ARIMA model types are listed using the standard notation of ARIMA(p,d,q)(P,D,Q), where p is the order of autoregression, d is the order of differencing (or integration), and q is the order of moving-average, and (P,D,Q) are their seasonal counterparts.

The Expert Modeler has determined that sales of men's clothing is best described by a seasonal ARIMA model with one order of differencing. The seasonal nature of the model accounts for the seasonal peaks that we saw in the series plot, and the single order of differencing reflects the upward trend that was evident in the data.

Model Summary

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Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.523	.	.523	.523	.523	.523	.523	.523	.523	.523	.523
R-squared	.823	.	.823	.823	.823	.823	.823	.823	.823	.823	.823
RMSE	3936.935	.	3936.935	3936.935	3936.935	3936.935	3936.935	3936.935	3936.935	3936.935	3936.935
MAPE	4.578	.	4.578	4.578	4.578	4.578	4.578	4.578	4.578	4.578	4.578
MaxAPE	18.929	.	18.929	18.929	18.929	18.929	18.929	18.929	18.929	18.929	18.929
MAE	3083.848	.	3083.848	3083.848	3083.848	3083.848	3083.848	3083.848	3083.848	3083.848	3083.848
MaxAE	10746.532	.	10746.532	10746.532	10746.532	10746.532	10746.532	10746.532	10746.532	10746.532	10746.532
Normalized BIC	16.810	.	16.810	16.810	16.810	16.810	16.810	16.810	16.810	16.810	16.810

The Model Fit table provides fit statistics calculated across all of the models. It provides a concise summary of how well the models, with reestimated parameters, fit the data. For each statistic, the table provides the mean, standard error (SE), minimum, and maximum value across all models. It also contains percentile values that provide information on the distribution of the statistic across models. For each percentile, that percentage of models have a value of the fit statistic below the stated value. For instance, 95% of the models have a value of MaxAPE (maximum absolute percentage error) that is less than 3.676.

While a number of statistics are reported, we will focus on two: MAPE (mean absolute percentage error) and MaxAPE (maximum absolute percentage error). Absolute percentage error is a measure of how much a dependent series varies from its model-predicted level

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and provides an indication of the uncertainty in your predictions. The mean absolute percentage error varies from a minimum of 0.669% to a maximum of 1.026% across all models. The maximum absolute percentage error varies from 1.742% to 4.373% across all models. So the mean uncertainty in each model's predictions is about 1% and the maximum uncertainty is around 2.5% (the mean value of MaxAPE), with a worst case scenario of about 4%. Whether
these values represent an acceptable amount of uncertainty depends on the degree of risk you are willing to accept.
Note : For the descriptive statistics of the model, R-squared represents the coefficient of good fit if the value is greater = 0.998 more than 0.05 this mean the model represent data exactly (good model) .

Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
والتجزئة الجملة تجارة -والفنادق والمطاعم Model_1	1	.523	20.924	17	.230	0

The model statistics table provides summary information and goodness-of-fit statistics for each estimated model. Results for each model are labeled with the model identifier provided in the model description table. First, notice that the model contains two predictors out of the five candidate predictors that you originally specified. So it appears that the Expert Modeler has identified two independent variables that may prove useful for forecasting.

Although the Time Series Modeler offers a number of different goodness-of-fit statistics, we opted only for the stationary *R*-squared value. This statistic provides an estimate of the proportion of the total variation in the series that is explained by the model and is preferable to ordinary *R*-squared when there is a trend or seasonal pattern, as is the case here. Larger values of stationary *R*-squared (up to a maximum

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value of 1) indicate better fit. A value of 0.948 means that the model does an excellent job of explaining the observed variation in the series.

The Ljung-Box statistic, also known as the modified Box-Pierce statistic, provides an indication of whether the model is correctly specified. A significance value less than 0.05 implies that there is structure in the observed series which is not accounted for by the model. The value of 0.984 shown here is not significant, so we can be confident that the model is correctly specified.

The Expert Modeler detected nine points that were considered to be outliers. Each of these points has been modeled appropriately, so there is no need for you to remove them from the series.

Note: (value of Sig. = 0.981) ,by Using residual error test, and when Sig value greater than 0.05 that means the data are random and valid for prediction .

ARIMA Model Parameters

					Estimate	SE	t	Sig.
الجملة تجارة والتجزئة والمطاعم والفنادق-Model_1	الجملة تجارة والتجزئة والمطاعم والفنادق	No Transformation	AR	Lag 2	-.490-	.147	-3.346-	.002
			Difference		1			
	السنوات	No Transformation	Numerator	Lag 0	-.049-	.009	-5.652-	.000
				Lag 5	-.049-	.009	-5.665-	.000
			Difference		1			

The ARIMA model parameters table displays values for all of the parameters in the model, with an entry for each estimated model labeled by the model identifier. For our purposes, it will list all of the variables in the model, including the dependent variable and any independent variables that the Expert Modeler determined were significant. We already know from the model statistics table that there are two significant predictors. The model parameters table shows us that they are the *Number of Catalogs Mailed* and the *Number of Phone Lines Open for Ordering*.

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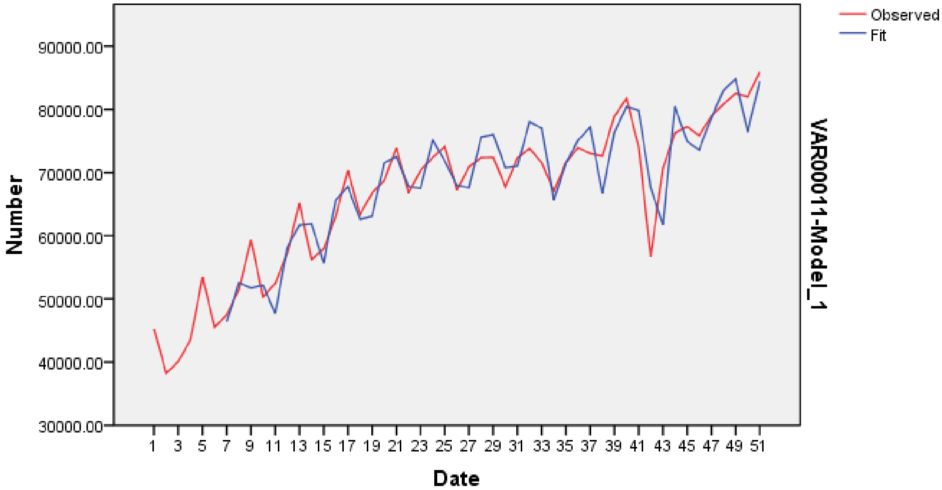
Note : This table provides an estimate of the coefficients of the model, from the model we note that the level of significance Sig= 0.00. Less than 0.05, which indicates that the coefficients are statistically significant, also effective and predictable .



The predicted values show good agreement with the observed values, indicating that the model has satisfactory predictive ability. Notice how well the model predicts the seasonal peaks. And it does a good job of capturing the upward trend of the data.

Note : As in the diagram we observe the compatibility between the observed and real values. Thus we have predicted a model that represents the data well by using all statistically significant measures .

Conclusion

For the descriptive statistics of the model, R-squared represents the coefficient of good fit if the value is greater **= 0.82** more than 0.05 this mean the model represent data exactly (good model) .

This table provides an estimate of the coefficients of the model, from the model we note that the level of significance Sig= 0.00. Less than 0.05, which indicates that the coefficients are statistically significant, also effective and predictable .

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