

Forecasting in Time Series Analysis

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Abstract:In this study, time series analysis theory and models have been examined. Utilizing methods for maximum likelihood estimation, fitting and forecasting time series can result in estimations and standard errors for parameter coefficients. Time series having both stochastic and deterministic seasonality can be forecasted using traditional forecasting models like ARIMA with great success.

Keywords: Forecasting, Time Series, maximum likelihood estimation, stochastic.

1. Introduction

The term "time series" refers to a chronological list of observations made regarding a single variable. The sample could be erratic, even if the observations are often made at regular intervals (days, months, years). The two steps in a time series analysis are as follows:

- (1) constructing a model that depicts a time series
- (2) confirming the proposed model
- (3) utilising the model to impute missing values or forecast future values.

A value in a time series should be a function of earlier values if it follows a predictable pattern. developing a time series model has the same objective as developing other kinds of predictive models: to produce a model with the smallest feasible error between the target variable's anticipated value and its actual value.

The main distinction between traditional models and time series models is that traditional models use other variables as predictors, and the concept of a lag value doesn't apply because the observations don't represent a chronological sequence. Time series models use lag values of the target variable as predictor variables, whereas traditional models use other variables as predictors.

Time series are seen as recordings of stochastic processes that change through time from a statistical perspective. We'll focus on the scenario in which observations are made at distinct, evenly spaced intervals of time.

The defining characteristic of time series is temporal dependence: the distribution of an observation at a given time point conditional on a previous value of the series depends on those prior observations' results, i.e., the results are not independent. Typically, we will model a time series over all non-negative integers in order to analyze it.

2. Theory and Models

The concept of stationarity is essential to time series. A time series is considered stationary if, roughly speaking, its behaviour does not change over time. This indicates, for instance, that the values typically fluctuate at a steady rate and that their variability is constant throughout time. The study of stationary series is essential because they have a strong theoretical foundation and well-understood behaviour. Although the majority of the time series we witness are obviously non-stationary, many of them have straightforward relationships with stationary time series.

In time series, it has long been customary to pay more attention to the initial two moments of the process than to the actual distribution of observations. The first two moments of the process contain all of the information if the process is normally distributed, and most of the statistical theory underlying time series estimators is asymptotic and frequently solely dependent on these first two moments.

The invariant property of stationarity, which is rather simple, states that the statistical properties of the time series do not vary throughout the course of time. For instance, while annual rainfall may vary from year to year, the average rainfall over two intervals of time with similar length will be about equal to the number of times that threshold is exceeded. Of course, this assumption might not hold up over a lengthy period of time. For instance, the general weather patterns are changing as a result of the climate change we are currently experiencing (we shall discuss nonstationary time series near the end of this course). The assumption of stationarity is, nonetheless, a very plausible one in many circumstances and during shorter time periods. In fact, the assumption that a time series is stationary is frequently used in the statistical analysis of a time series. There are two definitions of stationarity: stringent stationarity, which is a much stronger criterion and assumes the distributions are invariant over time, and weak stationarity, which simply considers the covariance of a process.

3. Fitting and Forecasting

Let's say we have found a specific model that seems to fit a particular time series. The identified model must now be fitted, and its fit must be evaluated.

Maximum likelihood estimation techniques can be used for fitting, producing estimates and standard errors for the parameter coefficients.

It is crucial to evaluate the fit of a model once it has been fitted to a collection of data. This is due to the significant dependence of our conclusions on the suitability of the fitted model. The typical method for determining the goodness of fit is to look at the residuals. Plotting the residuals and determining whether they resemble a white noise series is a straightforward diagnostic. Once a suitable model has been chosen, its unknown parameters have been estimated, and it has been determined that the model accurately

describes the data, we may move on to the challenge of predicting future values for the series.

Other Methods: Time series methods are based on the idea that historical data contains persistent patterns that may be discovered through quantitative analysis and will persist into the future. As a result, the forecasting effort is essentially reduced to a thorough examination of the past and the presumption that the same patterns and linkages will persist in the future. There are several time-series analysis and forecasting techniques, with the key differences being how past observations are connected to the predictions.

4. Short Time Series

When data are collected via an occasional survey due to experimental circumstances or expensive expenses, short time series may be all that are available. This type of data is plainly under sampled, and stochastic noise may mask certain significant temporal pattern characteristics. Traditional forecasting models like ARIMA have proven to be quite successful in predicting time series with both deterministic and stochastic seasonality. Analysts need enough historical data to carry out efficient model identification and estimation using typical ARIMA methodologies.

5. Estimating of Missing Data

The fundamental premise of numerical analysis is that the pattern of time series data represents the realisation of some unidentified function. In order to estimate the missing values, it is important to choose the best function to describe the data. We consider the time interval where the missing values occurred and assume that the behaviour of the time series data follows a polynomial function or mixture of polynomial functions. This can occasionally be the most challenging step in the analysing process. To determine the proper length of time interval to be taken into account, we must carefully study each of the contributing components.

Once a polynomial that fits the chosen set of points has been found, it is assumed that the polynomial and the function will act similarly over the given range. The values of the polynomial should be accurate predictions of the unknown function's values. However, if there are apparent local anomalies in the data, we must fit various polynomials to different parts of the data. Spline-like special polynomials are among them. We don't want to find a polynomial that perfectly matches the data for the majority of time series

data. The data set may originate from a series of experimental measurements that are prone to inaccuracy, or functions used to fit a collection of real values frequently produce differences. In these circumstances, the least squares method is typically applied. This approach finds a polynomial that is more likely to be close to the true values based on statistical theory.

6. Spatial Time Series

Research in statistical/econometric models that describe the spatio-temporal evolution of a single variable or multi-variable relationships in space and time has significantly increased during the last twenty years. The space-time autoregressive integrated moving average (STARIMA) model class is one example of this methodological development. Similarly, to ARIMA model building for univariate time series, STARIMA model building is based on the same three-stage procedure (identification–estimation–diagnostic checking) and it has been applied to spatial time series data from a wide variety of disciplines.

7. Summary

In the present paper, Theory and models in time series analysis have been studied. Fitting and forecasting in time series carried out using maximum likelihood estimation procedures which allows to produce both estimates and standard errors for the parameter coefficients. Traditional forecasting models like ARIMA have been shown very effective in forecasting time series with stochastic seasonality as well as deterministic seasonality.

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