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Research Article

VARIABLE EVALUATION OF ARMA MODELS WITH ARCH/GARCH ERRORS AND TIME SERIES FOR WEATHER FORECASTING

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Abstract

Implement the family of ARMA models with ARCH/GARCH errors. GARCH, Generalized Autoregressive Conditional Heteroskedastic, models have become important in the analysis of time series data. The parameter estimates are checked by several diagnostic analysis tools including graphical features and proposition tests. ARMA model is used in the weather forecasting in that the problem of propagation impairments due to rain, cloud, snow for obtaining the required performance. Rain affects the signal most and involved is absorption & scattering. Auto regressive Moving Average (ARMA) model is used to generate and predict the time series values for rain reduction. The predicated values obtained for different window size of the ARMA model and analysis the time series of the error occurrence.

Keywords: ARMA model, Garch/arch error, Time series, Time series analysis.

1. Introduction

A period arrangement is a growth of information efforts which are by and large checked just as in time breaks. Time arrangement expectation alludes to the procedure by which the estimations of a framework isgauge in light of the data acquired from the past and current information points. In visions, signal preparing, econometrics and numerical fund, a period procedure is a grouping of information focuses, measured normally at progressive time instants disconnected at uniform time pauses. Time arrangement examination contains techniques for dividing time arrangement information keeping in mind the end goal to separate important measurements and different attributes of the information. Time arrangement gauging is the utilization of a model to foresee future qualities in view of already watched values. Time arrangement is oftentimes plotted by means of line diagrams.

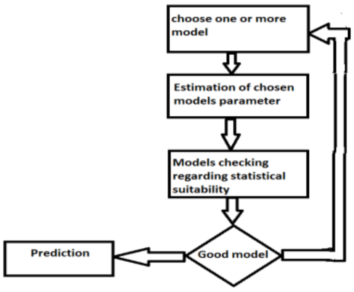

Fig: 1 Block diagram of model selection procedure.

2. Related Work

2.1 Autoregressive-Moving-Average Modeling

Autoregressive-moving-average (ARMA) models usually are numerical models of your tolerance, or maybe autocorrelation, in a very timeseries. ARMA models usually are usually used inside hydrology, dendrochronology, econometrics, along with grounds. There are lots of probable compensations of appropriate ARMA models to help info.

Modeling may give to understanding your actual program by simply discovery one thing in regards to the actual course of action which forms acceptance into your sequence. Intended for case, a simple actual water-balance product having precipitation since enter along with including terminology regarding evaporation, infiltration, along with groundwater storage space is usually shown to deliver any stream flow sequence since output which follows a positive form of ARMA product.

ARMA models they can double to help estimate conduct of an instance sequence through previous beliefs by yourself. This kind of prediction works extremely well like a baseline to gauge your credible need for other specifics towards program. ARMA models usually are traditionally used regarding prediction of monetary along with manufacturing occasion sequence. An additional using ARMA models can be simulation, during which artificial sequence with the entire very same tolerance framework as an discovered sequence is usually generated. Simulations are usually especially useful for established self-assurance time intervals regarding statistics along with believed time sequence amounts.

ARMA models they can double to eliminate tolerance. Throughout dendrochronology, for example, ARMA modeling can be practical regularly to come up with extra chronologies occasion series of ring width listing without any reliance on previous beliefs. This specific functioning, referred to as prewhitening, was created to eliminate biologically-related tolerance from the sequence in order that the extra could be significantly better regarding learning your influence of climate along with external environmental aspects with long growth.

3. Time Series Models

3.1. Autoregressive model

A time series *{Xt}* is said to be an autoregressive process of order *p* (abbreviated AR (*p*)) if it is a weighted linear sum of the past *p* values plus a random shock so that

$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + Z_t$ Equation. (1)

Where *{Zt}* denotes a purely random process with zero mean and variance σ^2_Z.

3.2. Moving average (MA) model:

A time series *{Xt}* is said to be a moving average process of order *q* (abbreviated MA (*q*)) if it is a weighted linear sum of the last *q* random shocks so that $X_t = Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q}$ Equation. (2)

Where *{Zt}* denotes a purely random process with zero mean and constant variance σ^2_z.

3.3 Extension to a GARCH(1,1)

Model In an ARCH(1) model, next period's variance only depends on last period's squared residual so a calamity that caused a large residual would not have the sort of persistence that we observe after actual crises. This has led to an extension of the ARCH model to a GARCH, orGeneralized ARCH model, which is similar in spirit to an ARMA model. In a GARCH(1,1) model.The great work hour of applied econometrics is the least squares model. The basic version of the model assumes that, the expected value of all error terms, in absolute value, is the same at any given point. Thus, the expected value of any given error term, squared, is equal to the variance of all the error terms taken together. This assumption is called homoskedasticity. Conversely, data in which the expected value of the error terms is not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, is said to suffer from heteroskedasticity.

It has long been recognized that heteroskedasticity can pose problems in ordinary least squares analysis. The standard warning is that in the presence of heteroskedasticity, the regression coefficients for an ordinary least squares regression is still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision.

However, the warnings about heteroskedasticity have usually been applied only to cross sectional models, not to time series models. For example, if one looked at the cross-section relationship between income and consumption in household data, one might expect to find that the consumption of low-income households is more closely tied to income than that of high-income households, because poor households are more likely to consume all of their income and to be liquidity-constrained. In a cross-section regression of household consumption on income, the error terms seem likely to be systematically larger for high-income than for low-income households, and the assumption of homoskedasticity seems implausible. In contrast, if one looked at an aggregate time series consumption function, comparing national income to consumption, it seems more plausible to assume that the variance of the error terms doesn't changed much over time.

3.4 Arch/Garch Models

Because this paper will focus on financial applications, we will use financial notation. Let the dependent variable be labeled r_t, which could be the return on an asset or portfolio. The mean value m and the variance h will be defined relative to a past information set. Then, the return r in the present will be equal to the mean value of r (that is, the expected value of r based on past information) plus the standard deviation of r (that is, the square root of the variance) times the error term for the present period.

The econometric challenge is to specify how the information is used to forecast the mean and variance of the return, conditional on the past information. While many specifications have been considered for the mean return and have been used in efforts to forecast future returns, rather simple specifications have proven surprisingly successful in predicting conditional variances. The most widely used specification is the GARCH(1,1) model introduced by Bollerslev (1986) as a generalization of Engle(1982). The (1,1) in parentheses is a standard notation in which the first number refers to how many autoregressive lags appear in the equation, while the second number refers to how many lags are included in the moving average component of a variable. Thus, a GARCH (1,1) model for variance looks like this:

$$h_t = \omega + \alpha h_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} .$$

This model forecasts the variance of date t return as a weighted average of a constant, yesterday's forecast, and yesterday's squared error. Of course, if the mean is zero, then from the surprise is simply r_{t-1}^2. Thus the GARCH models are conditionally heteroskedastic but have a constant unconditional variance.

3.5 Extensions and Modifications of GARCH

The GARCH(1,1) is the simplest and most robust of the family of volatility models. However, the model can be extended and modified in many ways. We will briefly mention three modifications. The GRACH(1,1)model can be generalized to a GARCH(p,q) model that is a model with additional lag terms such higher order models are often useful when a long span of data is used, like several decades of daily data or a year of hourly data. With additional lags, such models allow both fast and slow decay of information.

4. Result Analysis

4.1 Simulating and R_ARMA Time Series

Using the r program we plot the time series of the weather forecasting .The code is for

Goals: ARMA modeling - estimation, diagnostics, forecasting.# Make a R time series out of the raw data: specify frequency & start date gIIP<- ts

(raw data, frequency=12, start=c(2012,4))

print(gIIP) plot.ts(gIIP, type="l", col="blue", ylab="IIP Growth (%)", lwd=2,main="Full data")

grid()

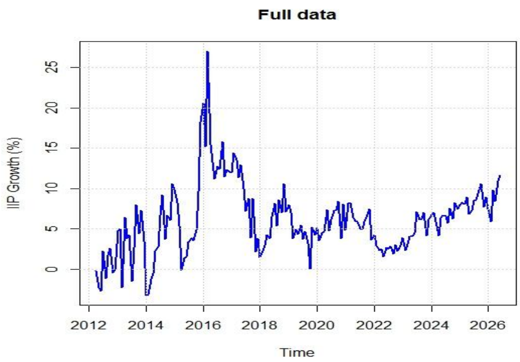

Fig: 2 Estimation of the IIP Growth in time series.

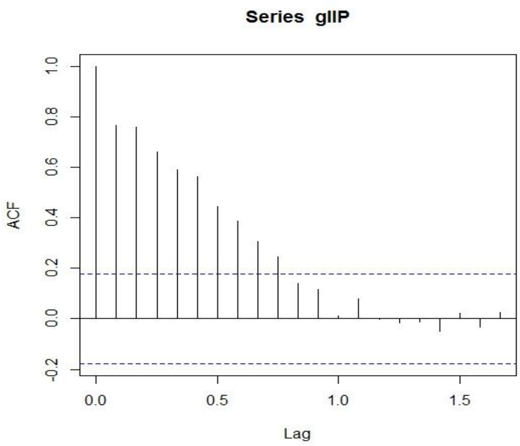

Fig:2 Diagnostics of the gIIP series.

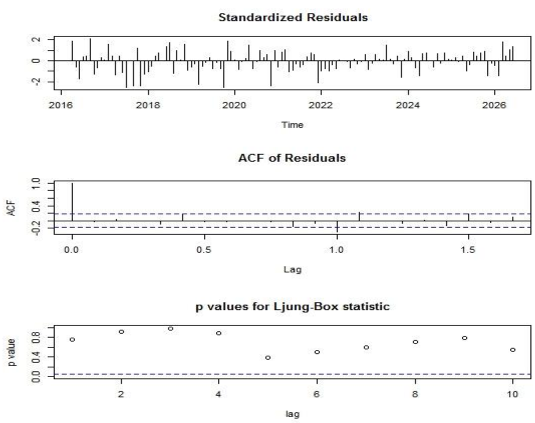

Fig :3 standardized residuals ,ACF of residuals p values of ljung statistic.

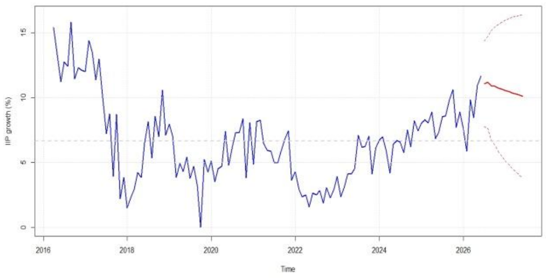

Fig:3 full data of the weather forecasting.

5. Conclusion

ARMA has gained a great popularity in time-series prediction because of its simplicity and reliability. The performance of GARCH and ARCH is compared. Compared to the ARMA the GRACH can more efficiently capture dynamic behavior of the weather temperature, resulting in a more compact and natural internal representation of the temporal information contained in the weather profile.

References

1. M. Sridhar 1, K. Padma Raju2, Ch. Srinivasa Rao3, D. Venkata Ratnam1,“ Prediction and Analysis of Rain Attenuation using ARIMA Model at Low latitude Tropical Station”,International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 2, Issue 7, July 2013.
2. A. Mauludiyanto, G. Hendrantoro, Member, IEEE, M. H. Purnomo, Member, IEEE, T. Ramadhany, and A. Matsushima, Member, IEEE “ARIMA Modeling of Tropical Rain Attenuation on a Short 28-GHz Terrestrial Link” IEEE ANTENNAS AND WIRELESS PROPAGATION LETTERS, VOL. 9, 2010.
3. S.Karthikeyan, S.Sasikumar, Principal, roever engineering college, perambalur, india. Efficient estimation algorithm for arma model for coloured noise s. Karthikeyanet. Al. Indian journal of computer science and engineering, Vol 1 no 2, 136-144
4. A. Beck, A. Ben-Tal, and Y. C. Eldar, “Robust mean-squared error estimation of multiple signals in linear systems affected by model and noise uncertainties,” Math Prog., B, Springer-Verlag, Dec.2009
5. Z. Ben-Haim and Y. C. Eldar, “Maximum set estimators with bounded estimation error” IEEE Transactions on Signal Processing ,Volume 53, Issue 8, Aug. 2005, pp. 3172 – 3182..
6. Don Johnson Signal Parameter Estimation. Version 1.4: Aug 18, 2003. The Connexions Project and licensed under the Creative Commons Attribution License Connexions module: m1126.
7. Y. C. Eldar and A. V. Oppenheim, “MMSE whitening and subspace whitening,” IEEE Transactions on Information Theory, vol. 49, July 2003, pp. 1846–1851.