FORECASTING SHORT TERM FINANCIAL DATA

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Abstract

This article suggests an imperial real world problem technique for forecasting the financial time series data in order to solve real problems. The financial data are forecasted via ARIMA model in order to give some future suggestion about the case study. Some stock market data have been obtained from the department of land and survey in Jordan. Thus, this was aimed at implementing this model.

Keywords: Financial time series, forecasting, ARIMA model

Introduction

Stocks markets forecasting is important for investors. However, it has gained much attention in financial data. Generally, forecasting stocks market has not been easy because different from demand series, price series present characteristics such as irregular mean and variance, and important outliers.

Particularly, commodity prices from financial stock markets data show asymmetrical behaviors similar to abrupt change and trends. Therefore, we need a suitable model in order to forecast these unusual features.

Researchers have implemented many mathematical models such as: curve fitting log transforms, differencing, Fourier transform, and wavelet transform to get a smooth data. Recently, ARIMA model have rapidly raised the short term forecasting processes. Consequently, Wall Street analysts have used ARIMA model as a mathematical models to forecast the future behavior of their financial data.

Therefore, to show the efficiency of ARIMA model in the context of forecasting, this paper launched this model to obtain some of the numerical and statistical results. This result is a useful indictor for investors in the land and survey sector. Moreover, in order to illustrate the effectiveness of this model, some data set were collected from the website: <u>http://www.dls.gov.jo/EN/index.php</u> (department of land and survey, Jordan). Furthermore, we considered a past time series data during the last two years (2013, 2014 and 2015) in order to forecast the behavior of the year

2016. Also, we noticed that the trading have decreased during this year compared to previous years. Therefore, we would like to see whether this decrease will continue in the next year Thus, this paper consists of 4 sections. Section 2 has some definitions, literature review, and mathematical concepts. Section 3 shows the empirical results and discussion, while section 4 presents the conclusion of this study.

Mathematical and Literature Reviews ARIMA Model

The purpose of non-linear regression to price forecasting has not been accounted so far. Other models of econometric modeling are uni-variate time series methods like Auto-regressive Moving Average (ARMA) [Swider and Weber, 2007; Contreras, et al., 2005]. ARMA is an appropriate model for the stationary time series data. Nevertheless, most of the software uses least stationary time series data. Nevertheless, most of the software uses least square estimation which requires stationary data. To conquer this problem and to allow ARMA model to handle non-stationary data, the researchers explore a special class for the non-stationary data. This model is called Auto-regressive Integrated Moving Average (ARIMA). This idea is to split a non-stationary series one or more times until the time series becomes stationary. After then, the fit model is found. ARIMA model has obtained very high attention in the scientific world. This model is popularized by George Box and Gwilym Jenkins in 1970s [Contreras, et al., 2005]. Furthermore, there are a huge number of ARIMA models which are ARIMA (p, q, d). However, P: order of autoregressive part (AR), d: degree of first differentiation (I), and q: order of the first moving part (MA). It should be noted that if no differencing is done (d = 0), then ARMA model can be gotten from ARIMA model [SAS, 2010; Spyros Makridakis, 1998; Al Wadi, 2011]. Thus, the equation for the simplest case ARIMA (1, 1, 1) is as follows: $(1-\Phi B)(1-B)Y_e = c + (1-\theta_1B)e_e$.

$$(1-\Phi_{B})(1-B)Y_{t} = c + (1-\theta_{B})e_{t}.$$

The model building process involves the following steps [Skander, 20021:

Model Identification

The first step is to determine whether the time series data is stationary or non-stationary. If the original series is non-stationary, the series is converted to stationary by differencing the series. The order of differencing is zero for a stationary series and is greater than zero for the non- stationary series.

Model Parameter Estimation

The estimation of parameters is very important in the model building. Therefore, the parameters obtained are estimated statistically by least square method.

Model Diagnostics

Before forecasting the series, it is necessary to check the adequacy of the tentatively identified model. The model is declared adequate if the residuals cannot improve forecast anymore. In other words, residuals are random.

Forecasting

Once the model adequacy is established, the series in question is forecasted for a specified period of time. It is always advisable to keep track of the forecast errors. Thus, depending on the magnitude of the errors, the model shall be re-evaluated. Therefore, in order to select the best ARIMA model, we should select the best criteria as mentioned below.

Methodology

The criteria which have been used to make a fair comparison can be presented in this subsection. The framework comparison can be presented in more details as follows:

We adopted the comparison of the performance of the models within two types of accuracy criteria: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Thus, these types of accuracy can be illustrated as (Aggarwal et al. (2008)):

1- Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (actual value-predicted value)^2}{N}}$$

2- Mean Absolute Percentage Error (MAPE). $MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\text{actual value-predicted value}}{\text{actual value}} \right|.100\%$

Where N represents the number of observations

ARIMA Model in Literature

ARIMA model has been used widely in many fields: humanity, sciences, medicine, engineering, and others. Consequently, Al Wadi and Ismail (2011) have forecasted financial time series dataset. Al Wadi et al. (2013) also forecasted insurance time series model based on Wavelet transform and ARIMA model. Moreover, Al Wadi et al. (2010) in their study forecasted the closed price dataset based on Wavelet Transform and ARIMA model.

Experimental Results and Conclusion

The minimum value of the used criteria is selected to decide the fit ARIMA model of the choice data from the department of land and survey.

All ARIMA models should be in 0,0,0 and 2,2,2. There are no need for more than the value (2,2,2), since it is not suitable mathematically. Also, more than the value is not considered since ARIMA model becomes valueless. Therefore, the best ARIMA model is selected as mentioned in the table below

Statistical fit	Year 2013	Year 2014	Year 2015	Year 2016
RMSE	1.2	1	0.8	2
MAPE	1.2%	0.9%	0.8%	1.3%

Table1. Fit ARIMA (p.d.g) model

Mathematically, the similar sample data is picked for fair comparison. The appropriate ARIMA model for predicting the sample data is also picked. For the year 2013, ARIMA (1,2,2) with RSME equal to 1.2 as presented in Table 1. However, the suitable ARIMA model in the year 2014 is ARIMA (1,2,1) with RMSE equal to 1. Similarly, the process forecasting accuracy give a suitable ARIMA (1,1,1) in the year 2015. Finally, Year 2016 will be similar to the three past years since the best ARIMA is 1,2,2 with RMSE equal to 2.

Empirically, the result in this article leads us to conclude that in the next year (2016), we will have the same result as the year 2013 to 2015. However, this is because the accuracy forecasting results are almost similar. Therefore, we recommend the department to change some of their policy in order to improve its forecasting accuracy and its income for the next year.

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