Hybrid ARIMA-GRACH Model

Auto-Regression Integrated Moving Average(ARIMA) model is a standard statistical model for time series forecast and analysis. It is specifically used for nonstatinay time series. Arima model shows that the current value of a variable can be explained in terms of two factors; a combination of lagged values of the same variable and a combination of a constant term plus a moving average of past error terms. Arima models are powerful and flexible, but they are unable to handle the volatility and nonlinearity that are present in the time series data. However, Generalized Autoregressive Conditional Heteroskedasticity(GARCH) time series models are widely used in econometrics and finance because they are designed to capture volatility clustering behavior. It attempts to explain the heteroskedastic behaviour of a time series as well as the serial influences of the previous values of the series and the noise terms. A GARCH model uses an autoregressive process for the variance itself, that is, it uses past values of the variance to account for changes to the variance over time. Combining these two models which called a Hybrid ARIMA-GARCH model may provide scope for preserving datatrend accross the forecast horizon while maintaining good prediction accuracy.

In order to recommend a hybrid ARIMA-GARCH model, two stages should be applied. In the first stage, we use the best ARIMA model that fits on stationary and linear time series data while the residuals of the linear model will contain the non-linear part of the data. In the second stage, we use the GARCH model in order to contain non-linear residuals patterns.

The hybrid ARIMA-GARCH model is a non linear time series model which combines a linear ARIMA model with the conditional variance of a GARCH model. The estimation procedure of ARIMA and GARCH models are based on maximum likelihood method. Parameters' estimation in logarithmic likelihood function is done through nonlinear Marquardt's algorithm.

ARIMA(p,d,q):

- AR: Autoregression. A model that uses the dependent relationship between an observation and some number of lagged observations.
- I:Integrated. The use of differencing of raw observations (i.e. subtracting an observation from an observation at the previous time step) in order to make the time series stationary.
- MA: Moving Average. A model that uses the dependency between an observation and residual errors from a moving average model applied to lagged observations.
- p: The number of lag observations included in the model, also called the lag order.
- d: The number of times that the raw observations are differenced, also called the degree of differencing.
- q: The size of the moving average window, also called the order of moving average.

GARCH(p,q):

The model includes lag variance terms (e.g. the observations if modeling the white noise residual errors of another process), together with lag residual errors from a mean process. The introduction of a moving average component allows the model to both model the conditional change in variance over time as well as changes in the time-dependent variance. Examples include conditional increases and decreases in variance.

- P: The number of lag variances to include in the GARCH model.
- q: The number of lag residual errors to include in the GARCH model.

Below are the three links I found using Hybrid ARIMA-GARCH model for prediction:

1. ARIMA+GARCH Trading Strategy on the S&P500 Stock Market Index Using R
https://www.quantstart.com/articles/ARIMA-GARCH-Trading-Strategy-on-the-SP500-Stock-Market-Index-Using-R/
2. Equity Return Modeling and Prediction Using Hybrid ARIMA-GARCH Model
https://pdfs.semanticscholar.org/f13a/e33c7aed5091f5d5d5ffc48ba044753c1474.pdf
3. The Performance of Hybrid ARIMA-GARCH Modeling and Forecasting Oil Price
https://www.econjournals.com/index.php/ijeep/article/view/6437/3672

SVMs

Support Vector Machines (SVMs) is a new powerful machine learning algorithm that maps the original data to a higher plane using a kernel function in order to optimize the process of prediction. The SVM has been widely used to predict the stock market trends since it is noise-tolerant and gives a decent accuracy. It is used for many classification and regression problems.In two dimensional space the hyperplane is a line. Based on the training samples, SVM classifies them into one of the different membership classes. While building the model, SVM training algorithm assigns new examples to one class or other class and assigns a hyperplane to output. This makes it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped such that the points in different categories are a a maximum distance from the decision boundary. SVM uses five-fold cross-validation technique to estimate probability estimates instead of a direct method. This makes it more expensive. They are effective in higher dimensions, especially when the number of dimensions exceeds the number of samples. This is due to the presence of hyperparameters which include gamma, regularization parameter and the choice of kernel available in the svm classifier. C decides the extent to which misclassification of data is allowed, gamma denotes how far influence of a training sample reaches and kernel which could be linear, poly or rbf which determines the learning of the hyperplane. SVMs may make classification errors within training data in order to minimize overall error across test data.

1. Walking through Support Vector Regression and LSTMs with stock price prediction https://towardsdatascience.com/walking-through-support-vector-regression-and-lstms-with-stock-price-prediction-45e11b620650

2. Comparison of Predictive Algorithms: Backpropagation, SVM, LSTM and Kalman Filter for Stock Market https://ieeexplore.ieee.org/document/8701258

3. Introduction to Support Vector Machines https://blog.quantinsti.com/support-vector-machines-introduction/