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Time Series Analisys

This is the report on the course final project for DSA 6100: Statistical Methods for Data Science and Analytics By

- Igor Ostaptchenko igor_ost@wayne.edu
- Ali Milhem gu5993@wayne.edu

The `R` source for this report is: arima.R The datasets:

- AAL Daily: data/stock_market_data-AAL.csv

Time Series Analisys

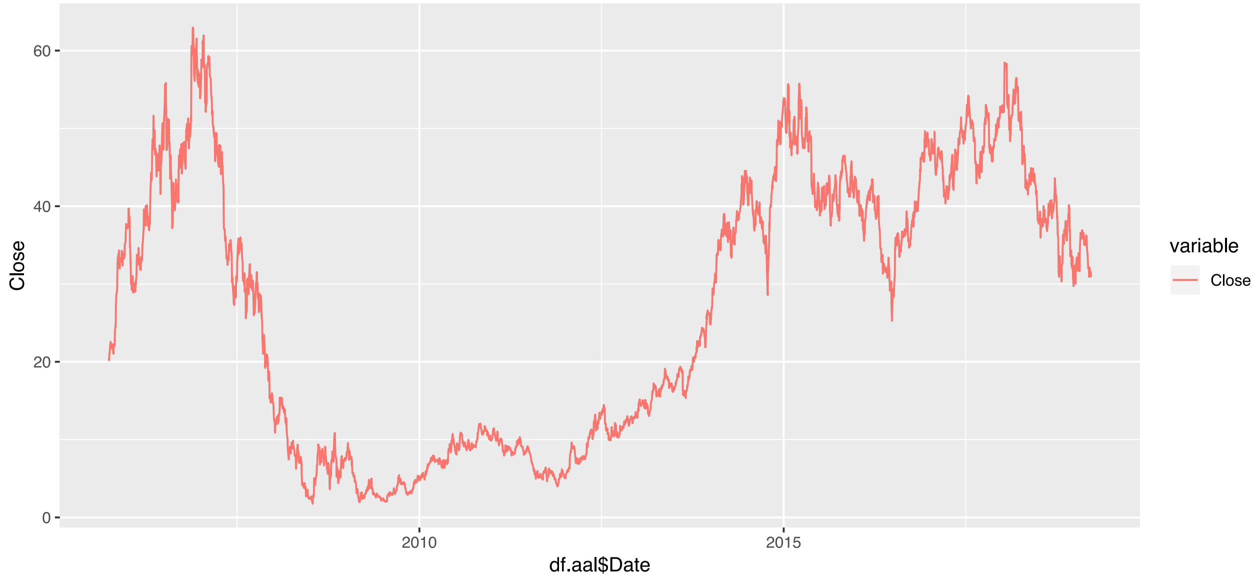
Time series is a series of data that occurs at a fixed intervals, for example: daily stock price, seasonal sales, etc. Time series analysis is the techniques of processing data based on the assumption that the successive values in the data represents measurements that take place in equal intevals. The purpose of time series analysis is to forecast future values of the time series variables.

Finantial data

Our purpose is to forcast the rate of return of American Airlines stock (AAL). We used the closing price starting from 09/27/2005 until 03/21/2019 as the basis f the analysis. We collected data from Yahoo Finance. The table include the following parameters: Date, Close, Open, High and Low.

AAL

American Airlines Group Inc (AAL) operates as a network air carrier; providing air transportation for passengers and cargo. As of December 31, 2018, the company operated a mainline fleet of 956 aircraft, whch makes it a major American airline company, and that is why we chose it for analysis. The data set is composed of the following parameters: Date: on which the price is given. High: is the highest price on that day. Low: is the lowest price on that day. Open: is the price at which the stock opened, when the stock market opened on that day. Close: is the closing price on that day when the market closed. We based our analysis on this parameter.



Fitting ARIMA

Stationarity

Let's asses the Stationarity of AAL `Close` price values

The Augmented Dickey-Fuller Test

For the daily `Close` prices of AAL time series :

```
> print(adf.test(df.aal$Close,alternative = "stationary"))

        Augmented Dickey-Fuller Test

data:  df.aal$Close
Dickey-Fuller = -1.4708, Lag order = 15, p-value = 0.8024
alternative hypothesis: stationary
```

Stationary of the time series means that the statistical properties of it does not change; it's mean and variance do not change. Based on the above test, we find the P-vale is high, which means that using ARIMA model to predict based on the price is not possible. Therefore, we will use `Returns` for prediction.

Moving focus to Arithmetic and Log Returns

Arithmetic Return: is calculated as the following: Rt = (Pt – Pt-1) / Pt-1 = Pt / Pt-1 – 1. Where: R: is the rate of return, t: time at which the return is calculated, Pt: the current price, Pt-1: the previous price.

Log Return: is calculated as the follwing formula: Rt = log(Pt / Pt-1) = log(Pt) – log(Pt-1). We use logarithms to calculate the return.

Transform `Close` prices to `Returns`

The `R` functions to calculate returns are as follows:

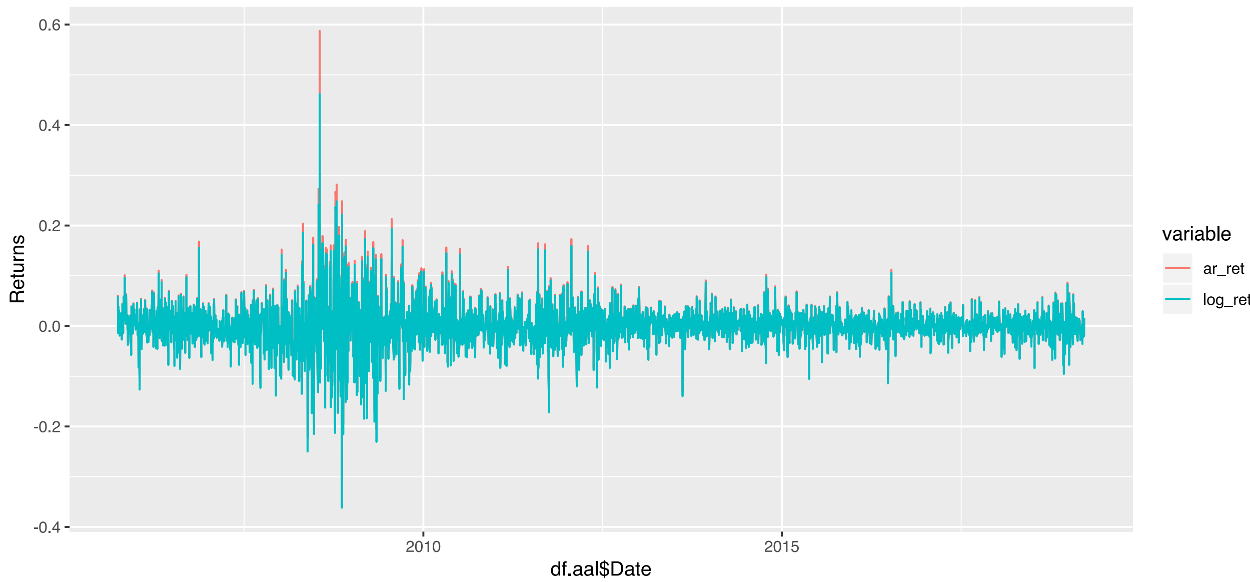
```
ar_ret <- function(P) {c(NA, P[2:length(P)]/P[1:(length(P)-1)] -1)}
log_ret <- function(P) {c(NA, log(P[2:length(P)]/P[1:(length(P)-1)]))}
```

These functions will be applyed to the `Close` price vector and create two more columns `ar_ret` and `log_ret`

```
> df.aal$ar_ret <- ar_ret(df.aal$Close)
> df.aal$log_ret <- log_ret(df.aal$Close)
> head(df.aal)
        Date Close      ar_ret     log_ret
1 2005-09-27 19.30          NA          NA
2 2005-09-28 20.50  0.06217617  0.06031979
3 2005-09-29 20.21 -0.01414634 -0.01424735
4 2005-09-30 21.01  0.03958436  0.03882098
5 2005-10-03 21.50  0.02332223  0.02305442
6 2005-10-04 22.16  0.03069767  0.03023593
```

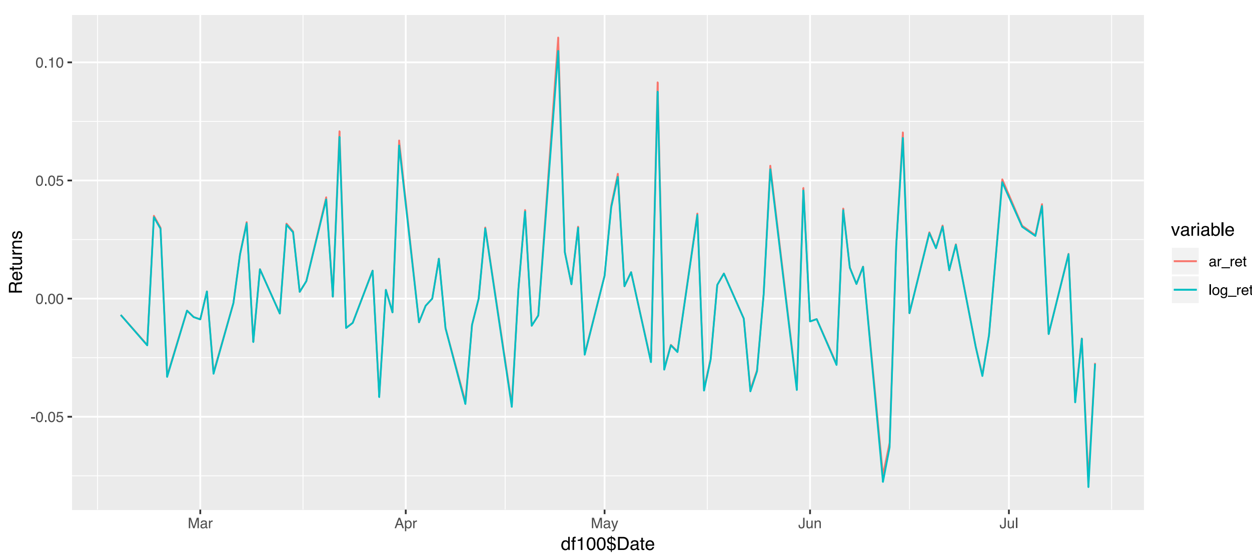
Notice that first row has blank returns. The first record will be dropped in future calculations

AAL



In the first chart (yearly scaled), we see that in 2008 there are outliers (extreme values) in the chart. Afterwards, the fluctioations continue to occure but withou outlier values,; within a dcreasing range until after the year of 2011. The other chart is for a different scale (monthly) which shows a stable trend.

Closer look on returns



The Augmented Dickey-Fuller Test on Returns

```
> # ADF test on ariphmetic return
> print(adf.test(df.aal$ar_ret, alternative = "stationary"))

        Augmented Dickey-Fuller Test

data:  df.aal$ar_ret
Dickey-Fuller = -13.646, Lag order = 15, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df.aal$ar_ret, alternative = "stationary") :
  p-value smaller than printed p-value
> # ADF test on log return
> print(adf.test(df.aal$log_ret, alternative = "stationary"))

        Augmented Dickey-Fuller Test

data:  df.aal$log_ret
Dickey-Fuller = -13.709, Lag order = 15, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(df.aal$log_ret, alternative = "stationary") :
  p-value smaller than printed p-value
```

Conclusion: the Arithmetic and Log Returns Time Series is stationary enough thus allowing to apply ARIMA class models to forecast the time series.

Use Auto.Arima

The `R` s `forecast` package provides `auto.arima` function to select best ARIMA model according to either AIC, AICc or BIC value. The function conducts a search over possible model within the order constraints provided.

The first 3000 returns of `AAL` dataset will be used to train the model.

Find the best model for 3000 observations of `AAL`

```
> aal.ar.autoarima <- auto.arima(df.aal[1:3000,]$ar_ret,
+                                max.order=300,
+                                trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2) with non-zero mean : -10161.53
 ARIMA(0,0,0) with non-zero mean : -10158.63
 ARIMA(1,0,0) with non-zero mean : -10161.04
 ARIMA(0,0,1) with non-zero mean : -10160
 ARIMA(0,0,0) with zero mean     : -10158.25
 ARIMA(1,0,2) with non-zero mean : -10158.91
 ARIMA(2,0,1) with non-zero mean : -10158.22
 ARIMA(3,0,2) with non-zero mean : -10164.8
 ARIMA(3,0,1) with non-zero mean : -10156.83
 ARIMA(4,0,2) with non-zero mean : -10155.13
 ARIMA(3,0,3) with non-zero mean : -10177.41
 ARIMA(2,0,3) with non-zero mean : -10154.9
 ARIMA(4,0,3) with non-zero mean : -10164.45
 ARIMA(3,0,4) with non-zero mean : -10164.72
 ARIMA(2,0,4) with non-zero mean : -10156.56
 ARIMA(4,0,4) with non-zero mean : -10162.49
 ARIMA(3,0,3) with zero mean     : -10177.19

 Now re-fitting the best model(s) without approximations...

 ARIMA(3,0,3) with non-zero mean : -10184.57

 Best model: ARIMA(3,0,3) with non-zero mean
```

For `ariphmetic` returns the best model is ARIMA(**ṗ** =3, **d** = 0, **r** = 3). Note that **d** is 0 because the `Returns` is already a differentiated measure.

Let's see about `Log Returns`

```
> aal.ar.autoarima.log <- auto.arima(df.aal[1:3000,]$log_ret,
+                                 max.order=300,
+                                 trace = TRUE)

 Fitting models using approximations to speed things up...

 ARIMA(2,0,2) with non-zero mean : -10229.61
 ARIMA(0,0,0) with non-zero mean : -10226.48
 ARIMA(1,0,0) with non-zero mean : -10228.72
 ARIMA(0,0,1) with non-zero mean : -10227.68
 ARIMA(0,0,0) with zero mean     : -10228.36
 ARIMA(1,0,2) with non-zero mean : -10226.69
 ARIMA(2,0,1) with non-zero mean : -10226.01
 ARIMA(3,0,2) with non-zero mean : -10239.06
 ARIMA(3,0,1) with non-zero mean : -10224.36
 ARIMA(4,0,2) with non-zero mean : -10220.88
 ARIMA(3,0,3) with non-zero mean : -10244.42
 ARIMA(2,0,3) with non-zero mean : -10222.57
 ARIMA(4,0,3) with non-zero mean : -10230.23
 ARIMA(3,0,4) with non-zero mean : -10230.58
 ARIMA(2,0,4) with non-zero mean : -10222.16
 ARIMA(4,0,4) with non-zero mean : -10246.03
 ARIMA(5,0,4) with non-zero mean : -10245.72
 ARIMA(4,0,5) with non-zero mean : -10247.3
 ARIMA(3,0,5) with non-zero mean : -10243.32
 ARIMA(5,0,5) with non-zero mean : -10245.82
 ARIMA(4,0,5) with zero mean     : -10249.5
 ARIMA(3,0,5) with zero mean     : -10245.2
 ARIMA(4,0,4) with zero mean     : -10240.45
 ARIMA(5,0,5) with zero mean     : -10246.98
 ARIMA(3,0,4) with zero mean     : -10232.42
 ARIMA(5,0,4) with zero mean     : -10248.12

 Now re-fitting the best model(s) without approximations...

 ARIMA(4,0,5) with zero mean     : -10250.27

 Best model: ARIMA(4,0,5) with zero mean
```

For `Log` returns the best model is ARIMA(**ṗ** = 4, **d** = 0, **r** = 5). Same: **d** is 0 because the `Log Returns` is already a differentiated measure.

Let's asses the selected model parameters.

Arithemtic returns fit

```
> print(summary(aal.ar.autoarima))
Series: df.aal[1:3000, ]$ar_ret
ARIMA(3,0,3) with non-zero mean

Coefficients:
         ar1     ar2      ar3      ma1      ma2     ma3    mean
      0.5436  0.5205  -0.8897  -0.5292  -0.4805  0.8788  0.0013
s.e.  0.0424  0.0552   0.0325   0.0440   0.0568  0.0374  0.0008

sigma^2 estimated as 0.001958:  log likelihood=5100.31
AIC=-10184.62   AICc=-10184.57   BIC=-10136.57

Training set error measures:
                        ME       RMSE        MAE MPE MAPE      MASE      ACF1
```

```
Training set -1.406339e-05 0.04419841 0.02888782 NaN  Inf 0.7071239 0.0137817
                        ME       RMSE        MAE MPE MAPE      MASE      ACF1
Training set -1.406339e-05 0.04419841 0.02888782 NaN  Inf 0.7071239 0.0137817
```

Forecasting AAL on Arithmetic Returns

Lets run the forecast for 14 days ahead with the Residuals check

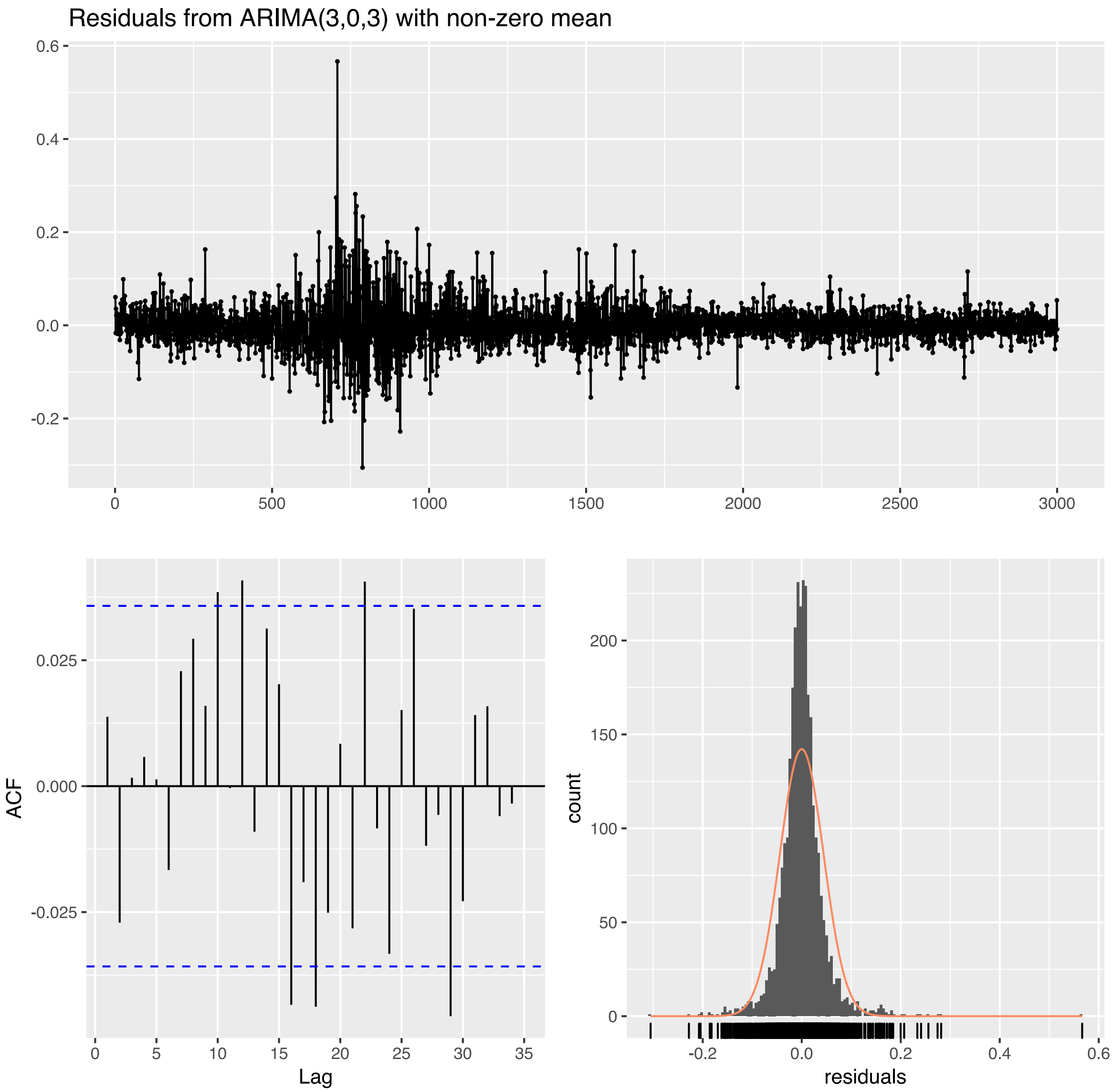
```
> f_ar <- forecast(aal.ar.autoarima, h= 14)
> checkresiduals(f_ar)

        Ljung-Box test

data:  Residuals from ARIMA(3,0,3) with non-zero mean
Q* = 13.101, df = 3, p-value = 0.004424

Model df: 7.   Total lags used: 10
```

Residuals of the Arithmetic Return Fit

A residual value is what is left ver after fitting a model. Residual values are equal to the difference between the observations and the corresponding fitted values: et=yt−^yt. In order for residual values to be useful, they should have the following properties:

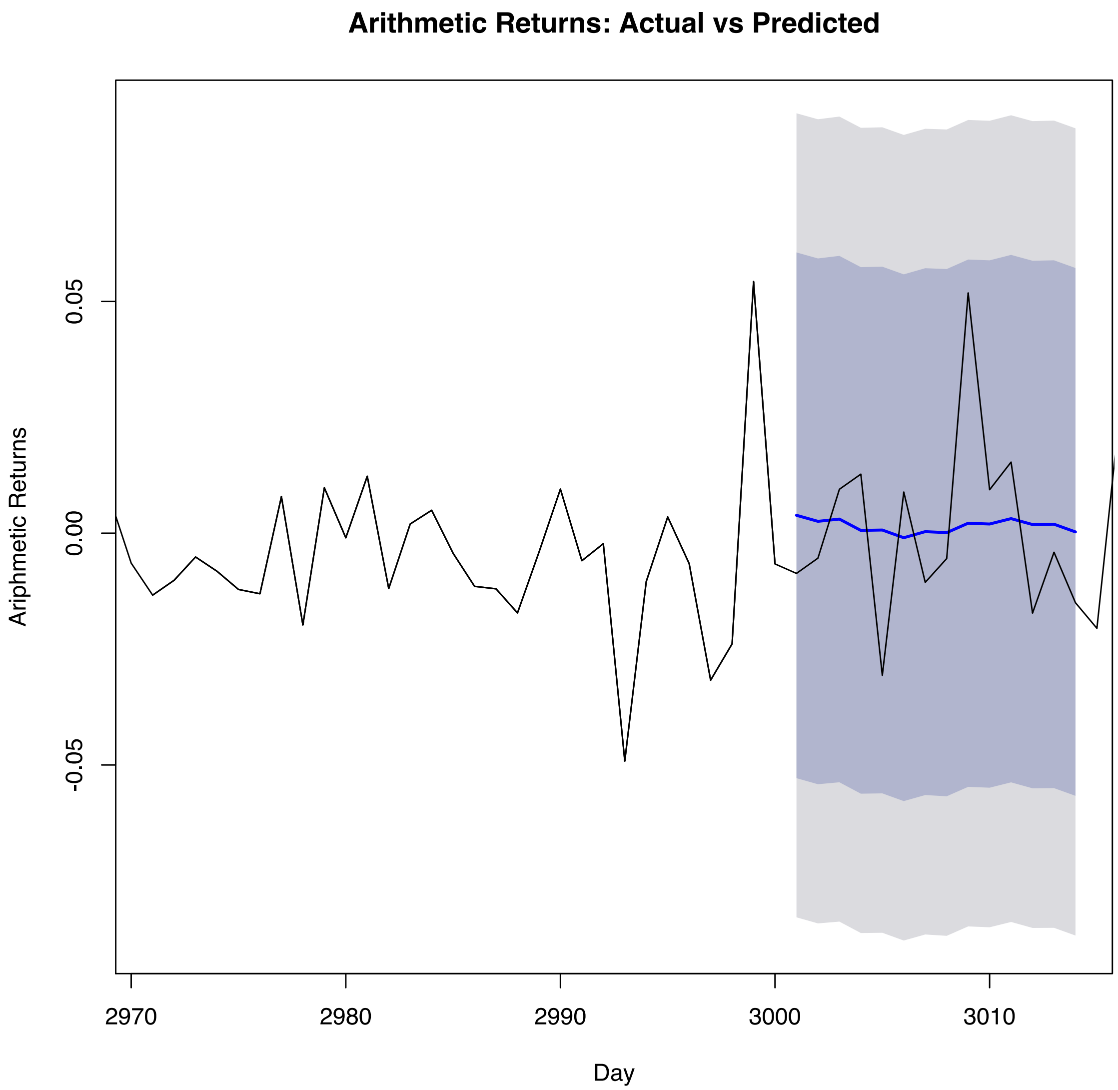
1. They sould not be correlated; otherwise, there is some information that is not used in the calculations.
2. The should not be biased, which means that the mean of them should not equal to zero; which is the case in our analysis.

Arithemtic Returns Fit Residuals:



The Arithemtic Return Forecast Errors

```
> accuracy(f_ar,x=df.aal[3001:3014,]$ar_ret)
                        ME       RMSE        MAE      MPE     MAPE      MASE      ACF1
Training set -1.406339e-05 0.04419841 0.02888782      NaN      Inf 0.7071239 0.0137817
Test set     -7.936604e-04 0.01879774 0.01475044 106.2668 106.2668 0.3610654        NA
>
```



Log Returns Fit

```
> print(summary(aal.ar.autoarima.log))
Series: df.aal[1:3000, ]$log_ret
ARIMA(4,0,5) with zero mean

Coefficients:
         ar1     ar2     ar3      ar4      ma1      ma2      ma3     ma4      ma5
      0.1674  0.1579  0.1176  -0.8557  -0.1406  -0.1308  -0.1099  0.8818  -0.0110
s.e.  0.2363  0.2416  0.1131   0.1287   0.2400   0.2168   0.0880  0.1263   0.0422

sigma^2 estimated as 0.001914:  log likelihood=5135.17
AIC=-10250.35   AICc=-10250.27   BIC=-10190.28

Training set error measures:
                     ME       RMSE        MAE MPE MAPE      MASE         ACF1
Training set 0.000267983 0.04368722 0.02885307 NaN  Inf 0.7083174 0.0007081013
                     ME       RMSE        MAE MPE MAPE      MASE         ACF1
Training set 0.000267983 0.04368722 0.02885307 NaN  Inf 0.7083174 0.0007081013
```

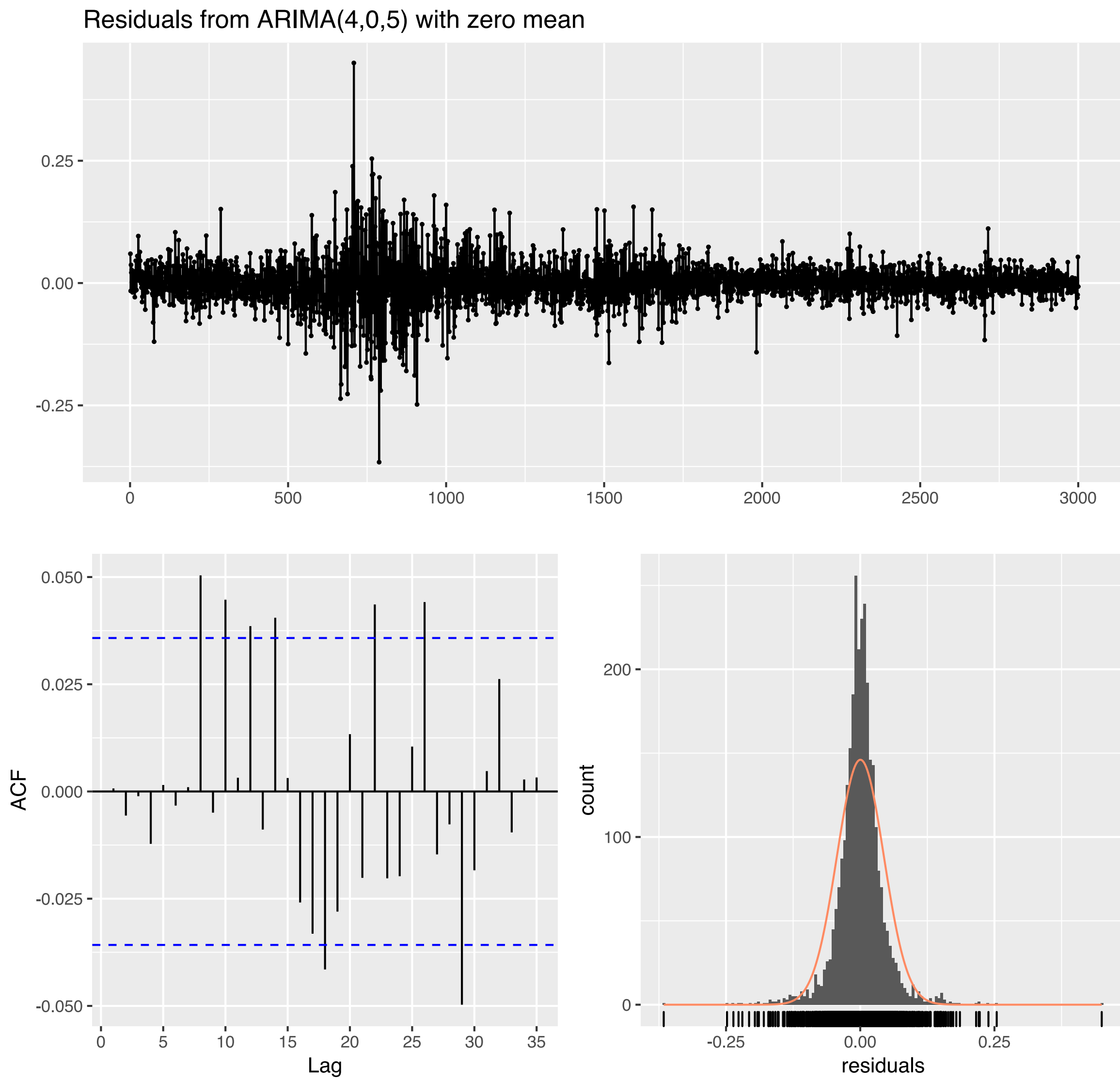
Forecasting AAL on Log Returns

Lets run the forecast for 14 days ahead with the Residuals check

```
> f_log <- forecast(aal.ar.autoarima.log,h=14)
> checkresiduals(f_log)

        Ljung-Box test

data:  Residuals from ARIMA(4,0,5) with zero mean
Q* = 18.839, df = 3, p-value = 0.0002952

Model df: 9.   Total lags used: 12
```

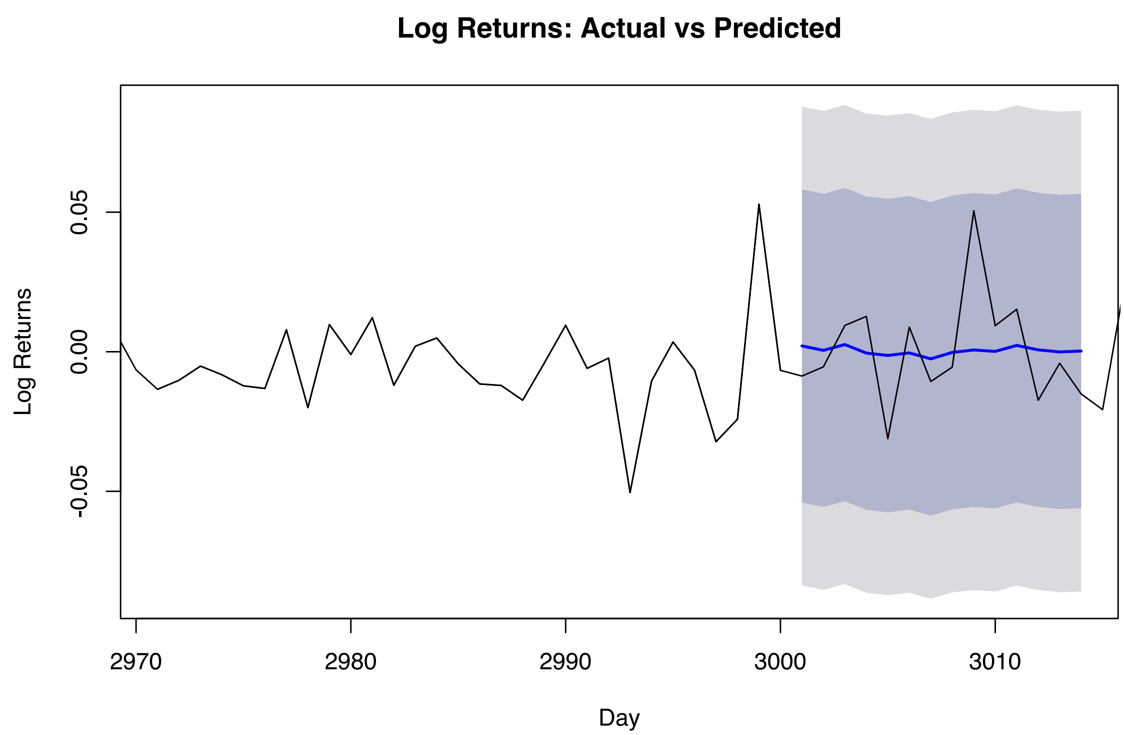
Residuals of the Log Return Fit

Log Returns Fit Residuals:



The Log Return Forecast Errors

```
> accuracy(f_log, x=df.aal[3001:3014,]$log_ret)
                       ME       RMSE        MAE      MPE     MAPE      MASE         ACF1
Training set 0.0002679830 0.04368722 0.02885307      NaN      Inf 0.7083174 0.0007081013
Test set     0.0002783467 0.01844228 0.01419282 97.74705 97.74705 0.3484213           NA
```



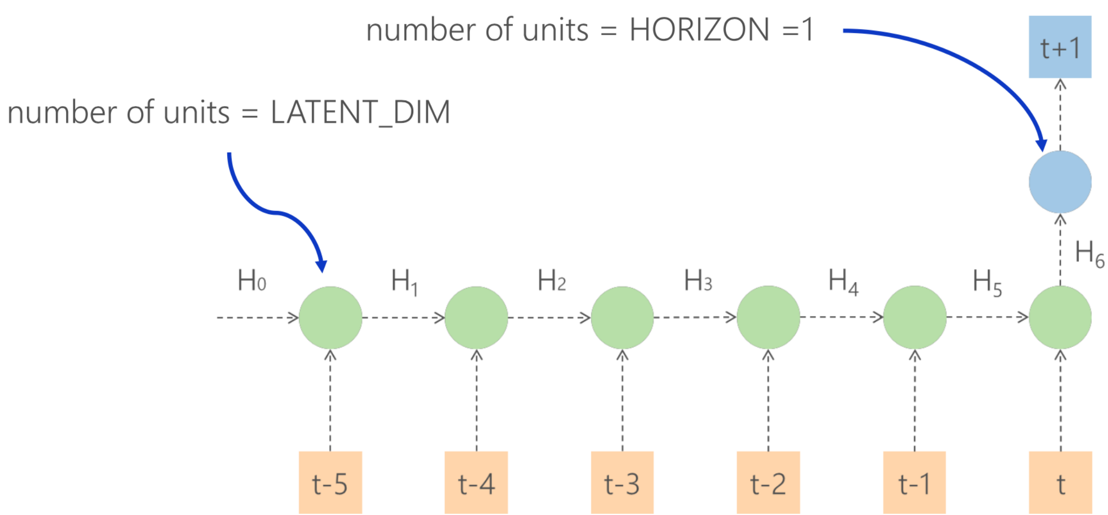
Conclusion

The Errors of the Log Return forecast smaller everywhere except Mean Errors. The `MPE` and `MAPE` rates are disturbing that is unfortunatelly confirmed by detail analisys of the `Log Returns: Actual vs Predicted` and `Arithmetic Returns: Actual vs Predicted` plots shown above: each line is the day and even visally the forecast errors are seen.

```
| Test Errors       |            ME |       RMSE |        MAE |      MPE |     MAPE |      MASE |
ACF1 |
|-------------------|---------------|------------|------------|----------|----------|-----------|----
--|
| Arithmetic Return | -7.936604e-04 | 0.01879774 | 0.01475044 | 106.2668 | 106.2668 | 0.3610654 | NA
|
| Log Return        |  0.0002783467 | 0.01844228 | 0.01419282 | 97.74705 | 97.74705 | 0.3484213 | NA
|
```

Fitting time series using ANN

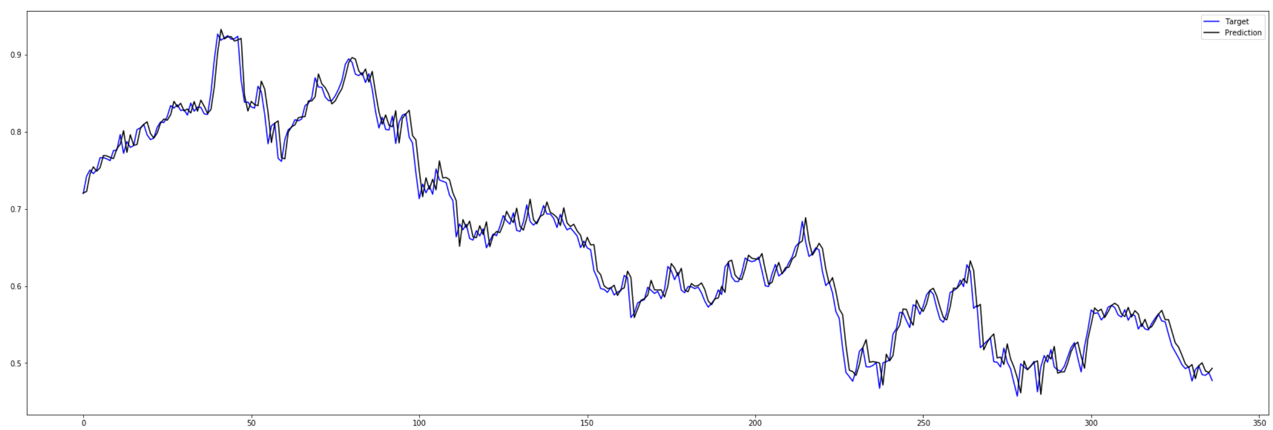
The Artificail Neural Network forecasting for the same `AAL` data is done in the python notebook. See: Jupiter Notebook. The input layer for ANN has the same number of inputs as the desired number of intevals we want to look back. The primitive model is shown in the picture bellow.



The data preparation is crutial steps and involves creating several aditional vectors for **ỳ**$_t$ and **ẋ**$_t$ for several values of **t** [**t**-7, **t**-8 ...]. The detailed decription is in Jupiter Notebook.

The RNN forecasting results

The following results were aquired running `RNN` with `GRU` cell for forecasting the stock prices. The price on the picture is `scaled` - this is typical for ANN to operate on valies scaled from `[0:1]` or `[-1:1]` :



RNN Forecasting Errors:

{'ME': -0.003913519198776012, 'RMSE': 0.01641030210773595, 'MAE': 0.012216668323480898, 'MPE': -0.6660415917080657, 'MAPE': 1.9340046033527194, 'MASE': inf}

Some values were not calculated

Conclusions

The error metrics compared in the table bellow:

Forecasting method	ME	RMSE	MAE	MPE	MAPE	MASE
ARIMA	0.0002783467	0.01844228	0.01419282	97.74705	97.74705	0.3484213
RNN	-0.0039135191	0.01641030	0.01221667	-0.666041	1.93400	-

While `RMSE`, `MAE` are at the same scale the ARIMA has shown less absolute value `ME`. Where `RNN` is superriour is in `MPE` and `MAPE`. The ARIMA error values for `MPE` and `MAPE` on this dataset renders it useles for predictions.

Overall in our opinion both methods are valuable options for the Time Series Forecasting. The ARIMA is more sensitive to data being non-stationary and financial data, unfortunatelly for ARIMA, has plenty of cases where the stationarity is possible to achive only by clever feature engineering. The some error measures in predictions of `Log Returns` were accepatble but ANN was able to acheave solid results on the four Price vectors. The ANN has an advantage in multivariate Time Series analisys: a few variables had been fed to network simultaniously and contributed to prediction. The literature suggests however, that succesfull applications of ARIMA is possible for datasets avalable in natural sciense. Both methods requred feature engeneering and data preparation to be usefull. The the process of creating aditional vectors and arrays are signigicantly more laborous for ANN: the amount of python code written is significant and possibility of erros increase in the absens of qualified data-sciense aware software engineers. The `R` function for `Arithmetic/Log Returns` has done the job for ARIMA fit in one line. Maybe with time the python libraries will be avaiable with the same level of abstraction avalable in `R` - the ultimate languge for statistical calculations. The 'R's ARIMA fit was done in signigicantly less time then training of ANN, that are more computationly intensive on the training phase. It will be interesting to see how ANN methods evolve to reach the `R`s ease of use and level of abstraction.

Literature

- https://github.com/borodark/wsu/blob/master/methods/casestudy/toc.md
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- Ratnadip Adhikari R. K. Agrawal, An Introductory Study on Time Series Modeling and Forecasting
- Analysis of Financial Time Series, Financial Econometrics, RUEY S. TSAY University of Chicago
- Tsay, Ruey S., An introduction to analysis of financial data with R/Ruey S. Tsay. p. cm. Includes index. ISBN 978-0-470-89081-3
- An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling, Shaojie Bai, J. Zico Kolter, Vladlen Koltun
- Temporal Convolutional Networks: A Unified Approach to Action Segmentation by Colin Lea Rene´Vidal Austin Reiter Gregory D. Hager, Johns Hopkins University
- A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series by Wen-Chuan Wang, Kwok-Wing Chau, Chun-Tian Cheng, Lin Qiu, Journal of Hydrology, Vol. 374, No. 3-4, 2009, pp 294–306
- https://people.duke.edu/~rnau/411diff.htm