Time Series Analysis & Forecasting

Analysis of Asianpaints stock price

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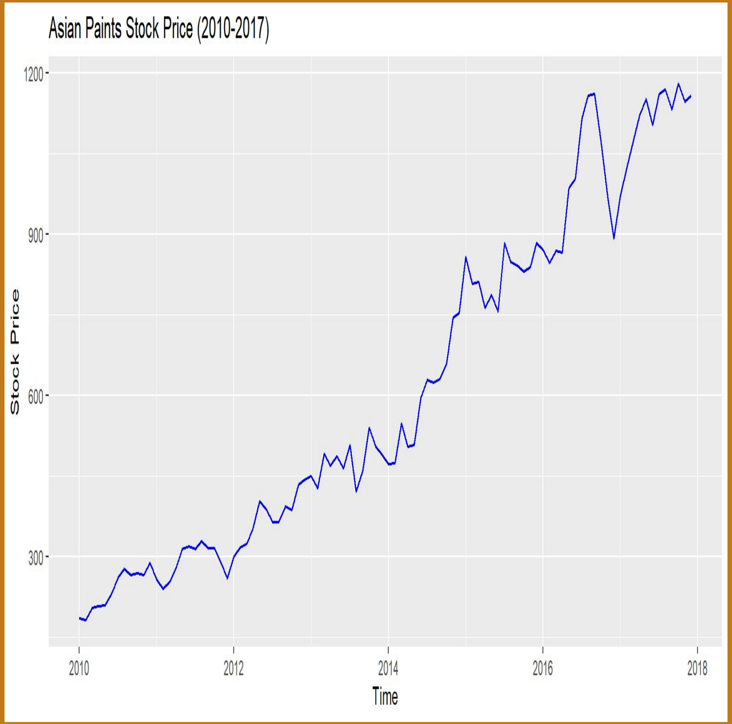
Introduction …

Company

Asian Paints is an Indian multinational paint company established in 1942. The company has been the market leader since 1967. It manufactures a wide range of paints for decorative and industrial use. The group has an enviable reputation in the corporate world for professionalism, fast track growth and building shareholder equity

About Dataset

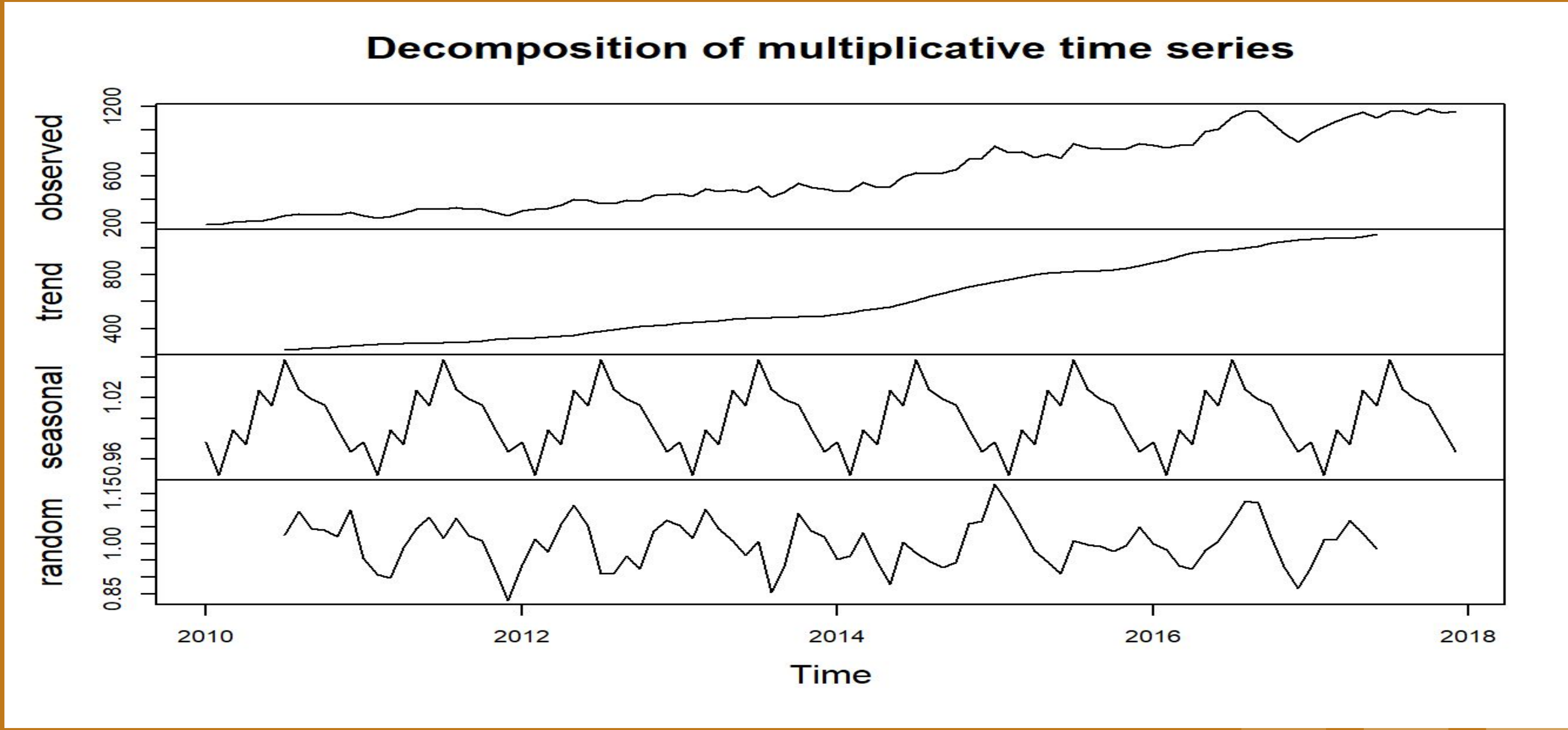
Our Dataset comprises of monthly closing price for the asian paints equity from 2010 till 2017. The source of the dataset is yahoo finance.



From the time plot, we can notice some important highlights :

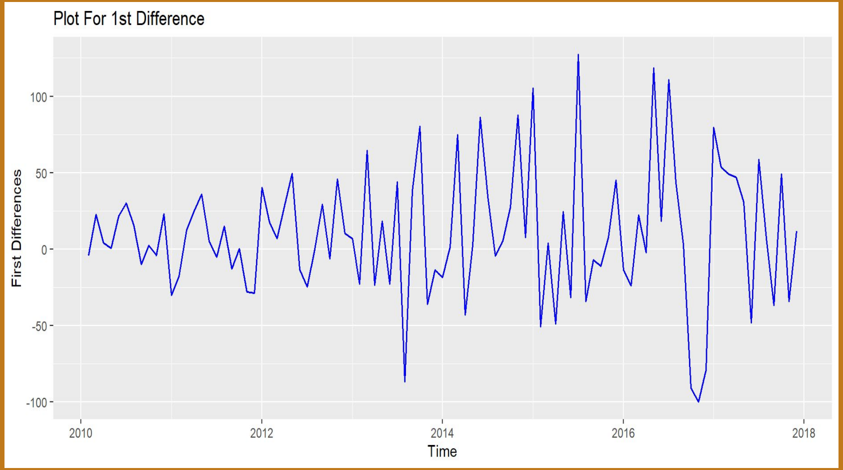
1. There is a consistent increase in stock prices which may imply that paint industry as a whole creating strong competitive oligopoly market.
2. Company is able to meet shift in consumer demand from traditional white-wash paints to odour free,dust and water resistant environmental friendly products.
3. Govt has sanctioned some funds which increases investment in real estate sector and will create positive impact on stock prices of company.

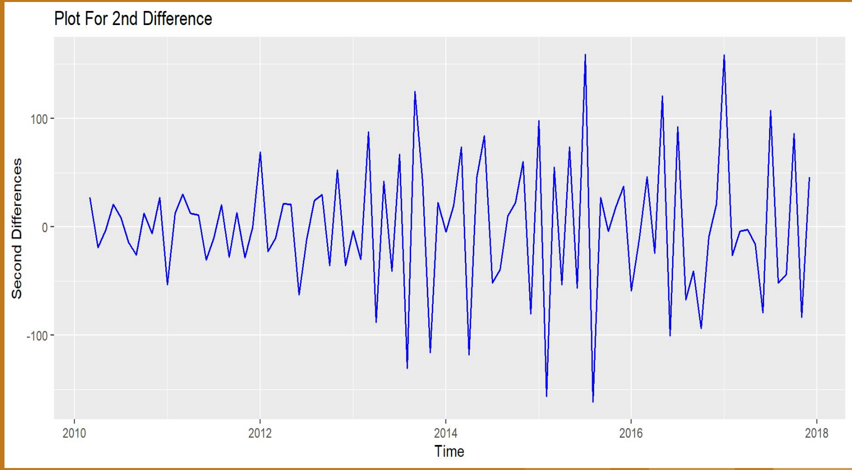
Decomposition of Time Series



Stationarity

From the time plot a pronounced trend is present So, we can not regard the original time series to be stationary. So, the first and second difference are obtained as:





Test For Stationarity

```
> adf.test(value.ts.d1,k=12)

        Augmented Dickey-Fuller Test

data:  value.ts.d1
Dickey-Fuller = -2.8888, Lag order = 12, p-value = 0.2094
alternative hypothesis: stationary
```

```
> adf.test(value.ts.d2,k=12)

        Augmented Dickey-Fuller Test

data:  value.ts.d2
Dickey-Fuller = -5.0344, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary
```

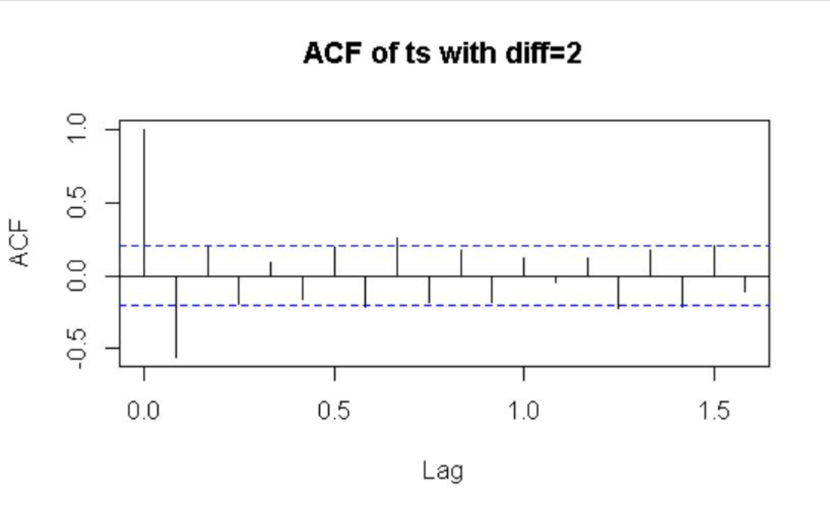
So in order to be sure which of the two differences will make the time series stationary we are applying Augmented Dickey Fuller Test

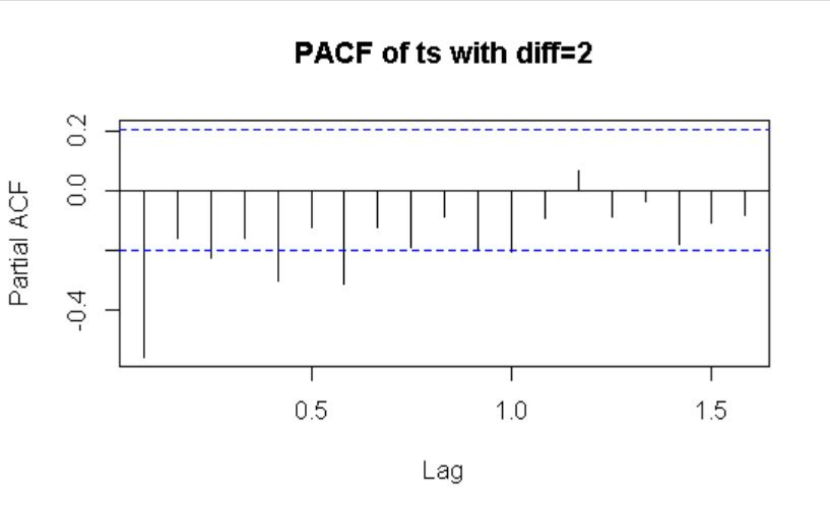
For the first difference the p-value for the test is much greater than 0.05. Hence, we conclude that the first difference is non stationary

But for the second differences the p-value for the test is much less than 0.05 implying enough evidence to conclude that the series is stationary

Hence, appropriate degree of differencing is 2

Sample ACF and PACF





These are the sample ACF and PACF of the 2nd differences of the time series. From here we can notice MA process of extent 7 can be chosen from the ACF plot and same with the AR process of extent 7 from PACF graph.

Simple Exponential Smoothing

Our Three Models

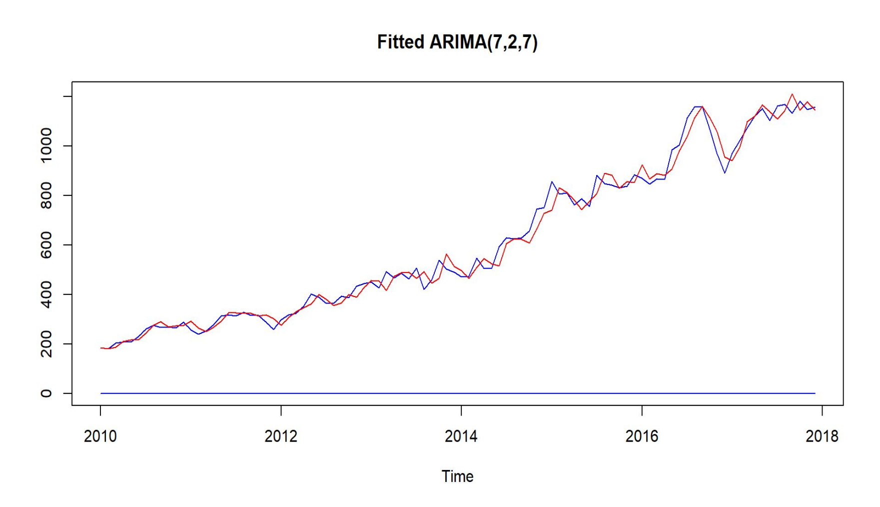
ARIMA (7,2,7)

SARIMA (1,1,1)(0,1,1)[12]

ARIMA(7,2,7)

So the idea behind fitting the ARIMA(7,2,7) comes from the sample only as our dataset has trend , Sample ACF is showing oscillatory behaviour implying the AR model is good ; Also from the ACF and the PACF the correlation coefficient are coming out to be significant so the appropriate choice of the model is ARIMA(7,2,7)

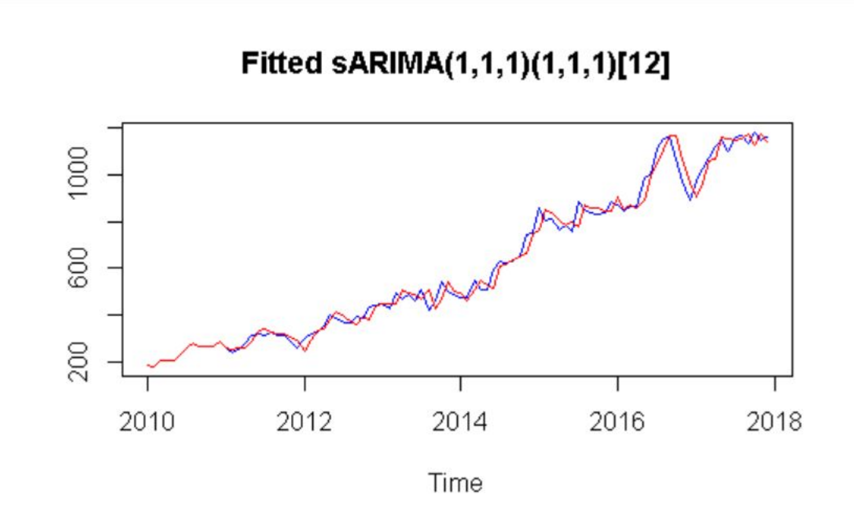
```
Call:
arima(x = close.ts, order = c(7, 2, 7))

Coefficients:
          ar1      ar2      ar3     ar4      ar5     ar6      ar7      ma1
      -0.3575  -0.5236  -0.5879  0.1344  -0.1843  -0.106  -0.2965  -0.7295
s.e.   1.6204   0.8388   0.4336  0.9121   1.2839   1.006   0.3131   1.6678
         ma2      ma3      ma4     ma5      ma6     ma7
      0.2541  -0.1346  -0.8764  0.3498  -0.0569  0.2670
s.e.  2.7015   1.5468   0.2092  2.0724   2.4346  0.9374

sigma^2 estimated as 1410:  log likelihood = -478.46,  aic = 986.91
```



SARIMA(1,1,1)(1,1,1)[12]

The Model 2.has been provided by the auto.arima function of R which is best fitted model for the given times series as we can observer the AIC value among all the other models is the lowest which We still need a in-depth analysis on these models before getting to a conclusion.

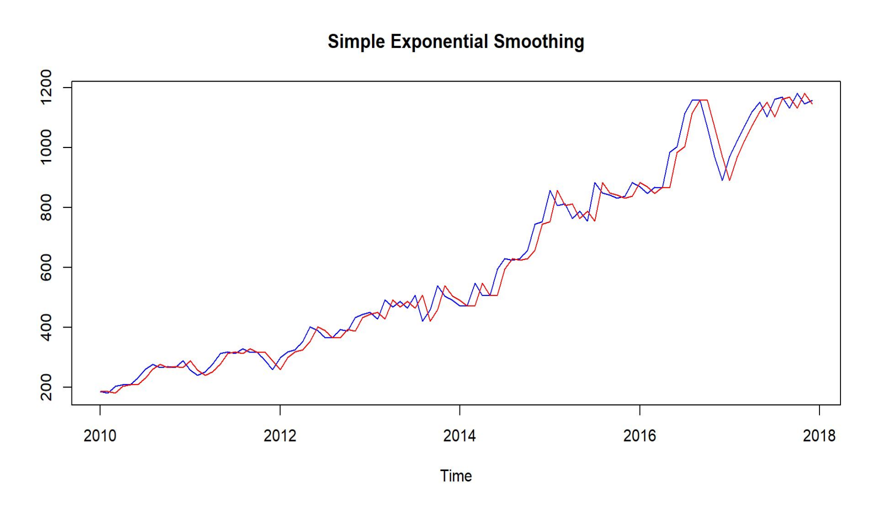
```
Call:
arima(x = values.ts, order = c(1, 1, 1), seasonal = list(order = c(1, 1, 1),
    period = 12))

Coefficients:
         ar1     ma1    sar1     sma1
      0.0050  0.0414  0.0247  -0.9948
s.e.  0.0174  0.0548  0.0437   0.0380

sigma^2 estimated as 1741:  log likelihood = -439.38,  aic = 888.77
>
```



Simple Exponential Smoothing

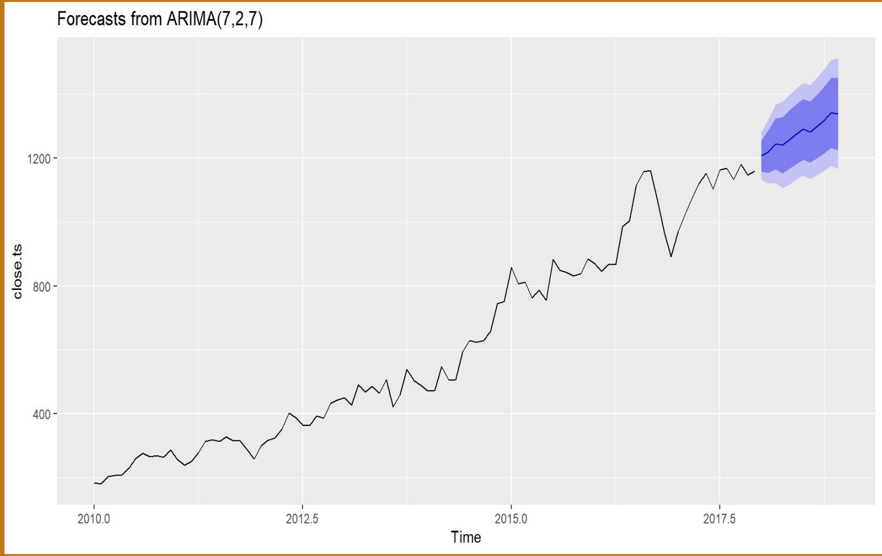
We use the smoothing constant as 0.99 as we want to give more weights / importance to the more recent values.

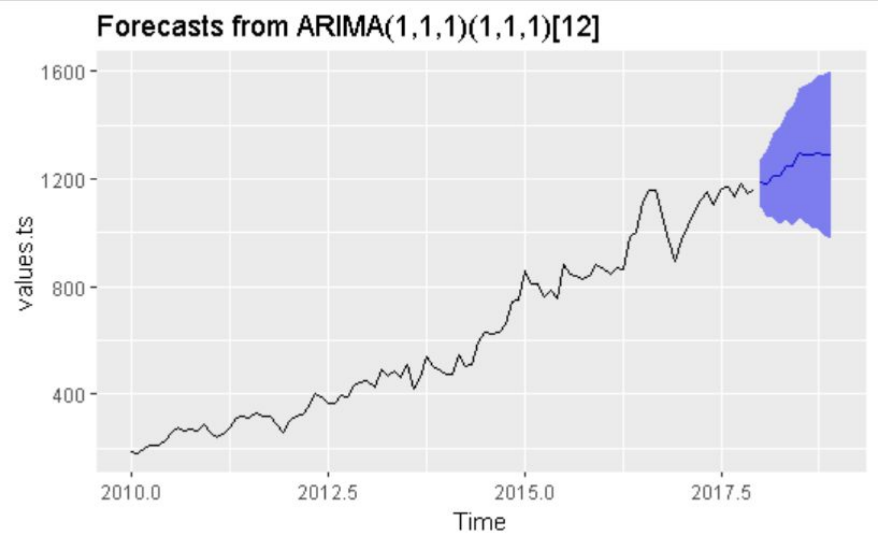
```
Forecast method: Simple exponential smoothing

Model Information:
Simple exponential smoothing

Call:
 ses(y = close.ts)

  Smoothing parameters:
    alpha = 0.9999

  Initial states:
    l = 185.1524

  sigma:  44.3216

     AIC     AICc      BIC
1170.119 1170.380 1177.812

Error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 10.14004 43.85744 32.37933 1.647439 5.599779 0.2550248 -0.04721369
```



Forecasting

Since, both ARIMA(7,2,7) and sARIMA(1,1,1)(1,1,1) has got AIC value and MSE less than that of the Simple Exponential Smoothing Method . Hence, we will use the above two models to forecast value for the next 12 months or say 1 year .





Comparing Forecasts

It is very evident from the below table that the sARIMA(1,1,1)(1,1,1)[12] is a better choice over ARIMA(7,2,7) for forecasting the values for future months

Model	MAE	MSE	RMSE
ARIMA(7,2,7)	65.00133	6969.088	83.48106
sARIMA(1,1,1)(1,1,1)[12]	61.81502	5177.404	71.95418

	observed	Forecasted ARIMA(7,2,7)	Forecasted sARIMA(1,1,1)(1,1,1)[12]
Jan	1131.05	1206.285	1181.56
Feb	1118.85	1220.085	1176.118
Mar	1120.7	1243.541	1207.835
Apr	1200.15	1240.134	1206.784
May	1305.6	1256.728	1241.199
Jun	1264.1	1273.869	1243.912
Jul	1448.3	1289.644	1290.083
Aug	1371.1	1281.389	1285.541
Sep	1294.05	1298.809	1285.684
Oct	1227.25	1316.807	1293.196
Nov	1344.9	1340.844	1284.474
Dec	1373.7	1338.357	1282.79

Thank You!