### VAR\_Model\_Clem\_v1

Steps for VAR Modeling -

- 1. Seasonally adjust the data
- 2. Individual ARIMA models, both time series needs to be I(1) process. Interpret ACF, PACF, Residuals White noise plots?
- 3. ADF and KPSS test -> Not stationary.
- 4. Johanessen test for cointegration.
- 5. VAR Model Train / test prediction error

Read seasonally adjusted data for modeling

```
library(tseries)
library(xlsx)

## Loading required package: rJava
## Loading required package: xlsxjars
```

```
library(forecast)
```

```
## Loading required package: zoo
##
## Attaching package: 'zoo'
##
## The following objects are masked from 'package:base':
##
## as.Date, as.Date.numeric
##
## Loading required package: timeDate
## This is forecast 5.9
```

```
setwd("/Users/kevalshah/Keval_Backup/University/UChicago/Capstone/Data/Data Clean up/Clean data to be used f
or Analysis")

options(java.parameters = "-Xmx1000m")

clem_data_social <- read.xlsx("clem_social_seasonally_adjusted_v1_average_weekly.xlsx", sheetName = "Seasona
lly Adjusted data")

# subset the data to have include observations that have both sales and social media data

clem_data_social_ts <- clem_data_social[1:260,]
head(clem_data_social_ts)</pre>
```

```
##
     Analysis_Date clemBlogSeasonallyAdjusted clemFacebookSeasonallyAdjusted
        2010-01-03
## 1
                                      581.6909
                                                                     -74.357581
## 2
        2010-01-10
                                      942.6203
                                                                    -140.438351
## 3
        2010-01-17
                                      505.8102
                                                                    -158.056139
## 4
        2010-01-24
                                      527.6058
                                                                     -45.693158
## 5
        2010-01-31
                                      569.3438
                                                                     -14.529697
## 6
        2010-02-07
                                      629.9015
                                                                       4.919822
##
     clemTwitterSeasonallyAdjusted clemCommentsSeasonallyAdjusted
## 1
                         -1464.1786
                                                          -3.356490
## 2
                         -2532.8262
                                                          -2.658894
## 3
                         -1907.9080
                                                         -12.057933
## 4
                         -1636.2469
                                                         -21.456971
## 5
                         -1177.8623
                                                          -2.800721
## 6
                          -524.3407
                                                          -5.286298
##
     clemReviewsSeasonallyAdjusted clemForumsSeasonallyAdjusted
## 1
                         -22.712518
                                                       -148.30772
## 2
                          -5.244249
                                                       -297.93560
## 3
                                                       -196.14474
                           2.087482
## 4
                          -2.549538
                                                       -106.06060
## 5
                           5.231712
                                                         96.99228
##
                           4.123539
                                                        256.67978
##
     Total.social.media
## 1
             -1131.2220
## 2
             -2036.4831
## 3
             -1766.2691
## 4
             -1284.4013
## 5
              -523.6249
               365.9977
## 6
```

```
# Read seasonally adjusted Clementine sales volume data

clem_data_sales <- read.xlsx("clem_social_seasonally_adjusted_v1_average_weekly.xlsx", sheetName = "Clem Sal
es Volume")

myvars = c("Date", "salestszSeasonallyAdjusted")

clem_data_sales_ts <- clem_data_sales[myvars]
head(clem_data_sales_ts)</pre>
```

```
## Date salestszSeasonallyAdjusted
## 1 2010-01-09 2077991.2
## 2 2010-01-16 1320663.6
## 3 2010-01-23 1909651.8
## 4 2010-01-30 689723.6
## 5 2010-02-06 1220800.4
## 6 2010-02-13 979856.2
```

ARIMA Model

```
# Function
        fun.illustrate.2=function(data,nperiod,p,d,q,P,D,Q) {
               error.holdout = rep(0,nperiod)
               r.sq.error.holdout = rep(0, nperiod)
               for(i in 1:nperiod) {
                       \# Keeping the first week as hold out for i[1] and then increment until 52nd value
                       # 52nd value = 52 week = 1 year i.e last year as hold out.
                      cutoff = length(data) - i
                       #cutoff = cutoff - i
                       #yvec.train=as.vector(data)[1:cutoff]
                               if(cutoff >= nperiod) {
                               yvec.train=as.vector(data)[1:cutoff]
                               #break:
                               yvec.hold=as.vector(data)[(cutoff+1):length(data)]
                               #yvec.hold
                               y=ts(yvec.train, start=2010, frequency=52)
                               pred=predict(arima(y, order = c(p,d,q), seasonal = list(order = c(P,D,Q))), n.ahead = (length(data)-cut) = (leng
off))
                               # Predicted - Actual? or Actual - predicted.
                               error.holdout[i]=mean((pred$pred-yvec.hold)^2)
                               if(length(pred$pred) > 1) {r.sq.error.holdout[i] = (cor(pred$pred,yvec.hold))^2}
                               #residuals.holdout[i] = yvec.hold - pred$pred
                       }
                # Ignore R Square of the i = 1 when holdout is last week.
                #return(list(error.holdout=error.holdout, Average = (error.holdout)^(1/length(error.holdout))))
               return(list(error.holdout=error.holdout, Average = mean(error.holdout), R.Squared = r.sq.error.holdout,
length(pred$pred), length(yvec.hold)))
               \#predict(arima(y, order = c(p,d,q), seasonal = 1ist(order = c(P,D,Q))), n.ahead=12)$predict(arima(y, order = c(p,d,q), seasonal = 1ist(order = c(P,D,Q))), n.ahead=12)$predict(arima(y, order = c(p,d,q), seasonal = 1ist(order = c(P,D,Q))), n.ahead=12)$predict(arima(y, order = c(p,d,q), seasonal = 1ist(order = c(P,D,Q))), n.ahead=12)$predict(arima(y, order = c(p,d,q), seasonal = 1ist(order = c(P,D,Q))), n.ahead=12)$predict(arima(y, order = c(p,d,q), seasonal = 1ist(order = c(P,D,Q))), n.ahead=12)$predict(arima(y, order = 
               \#predict(arima(y, order = c(p,d,q), seasonal = list(order = c(P,D,Q))), n.ahead=12)
       }
```

ARIMA for Clementine Social Media Mentions

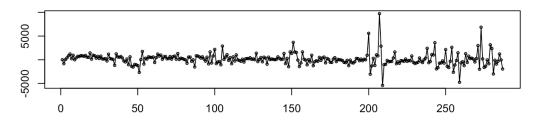
```
# Clementines Social Media Mentions
f1<- fun.illustrate.2(clem_data_social$Total.social.media,52, 2,0,0,0,0,0)
f2<- fun.illustrate.2(clem data social$Total.social.media,52, 2,0,1,0,0,0)
f3<- fun.illustrate.2(clem_data_social$Total.social.media,52, 2,0,2,0,0,0)
f4<- fun.illustrate.2(clem_data_social$Total.social.media,52, 2,1,1,0,0,0)
f5<- fun.illustrate.2(clem_data_social$Total.social.media,52, 2,1,2,0,0,0)
f6<- fun.illustrate.2(clem data social$Total.social.media,52, 2,1,0,0,0,0)
f7<- fun.illustrate.2(clem data social$Total.social.media,52, 2,2,0,0,0,0)
f8<- fun.illustrate.2(clem_data_social$Total.social.media,52, 2,2,1,0,0,0)
f9<- fun.illustrate.2(clem_data_social$Total.social.media,52, 2,2,2,0,0,0)
f10<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,0,0,0,0,0)
f11<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,0,1,0,0,0)
f12<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,0,2,0,0,0)
f13<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,1,1,0,0,0)
f14<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,1,2,0,0,0)
f15<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,1,0,0,0,0)
f16<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,2,0,0,0,0)
f17<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,2,1,0,0,0)
f18<-fun.illustrate.2(clem_data_social$Total.social.media,52, 1,2,2,0,0,0)
## Warning in log(s2): NaNs produced
f19<-fun.illustrate.2(clem data social$Total.social.media,52, 0,0,0,0,0,0)
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
```

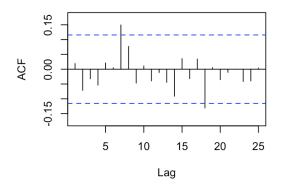
```
f20<-fun.illustrate.2(clem data social$Total.social.media,52, 0,0,1,0,0,0)
f21<-fun.illustrate.2(clem_data_social$Total.social.media,52, 0,0,2,0,0,0)
f22<-fun.illustrate.2(clem data social$Total.social.media,52, 0,1,0,0,0,0)
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
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## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
```

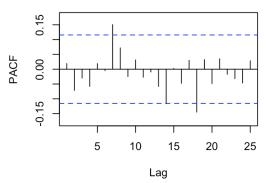
```
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
f24<-fun.illustrate.2(clem_data_social$Total.social.media,52, 0,1,2,0,0,0)
f25<-fun.illustrate.2(clem_data_social$Total.social.media,52, 0,2,0,0,0,0)
f26<-fun.illustrate.2(clem_data_social$Total.social.media,52, 0,2,1,0,0,0)
f27<-fun.illustrate.2(clem_data_social$Total.social.media,52, 0,2,2,0,0,0)
# Concatenate
total.social_media <- c(f1$Average, f2$Average, f3$Average, f4$Average, f5$Average, f6$Average, f7$Average,
f8$Average,f9$Average, f10$Average, f11$Average, f12$Average, f13$Average, f14$Average, f15$Average, f16$Ave
rage, f17$Average, f18$Average, f19$Average, f20$Average, f21$Average, f22$Average, f23$Average, f24$Averag
e, f25$Average, f26$Average, f27$Average)
# Minimum
summary(total.social_media)
               1st Ou.
       Min.
                          Median
                                      Mean
                                             3rd Ou.
                                                          Max.
## 5.122e+06 5.631e+06 6.400e+06 7.654e+07 7.189e+06 1.134e+09
which.min(total.social_media)
## [1] 13
# Auto ARIMA (2,1,2)
auto.total.social.media <- auto.arima(clem_data_social$Total.social.media)</pre>
auto.total.social.media
## Series: clem data social$Total.social.media
## ARIMA(2,1,2)
##
## Coefficients:
##
            ar1
                     ar2
                              ma1
                                      ma2
##
         1.3254 -0.3817 -1.7204 0.7322
                  0.0966
                           0.1138 0.1051
## s.e. 0.1317
## sigma^2 estimated as 1737494: log likelihood=-2460.74
## AIC=4931.47 AICc=4931.69
                               BIC=4949.75
```

tsdisplay(residuals(auto.total.social.media))

#### residuals(auto.total.social.media)

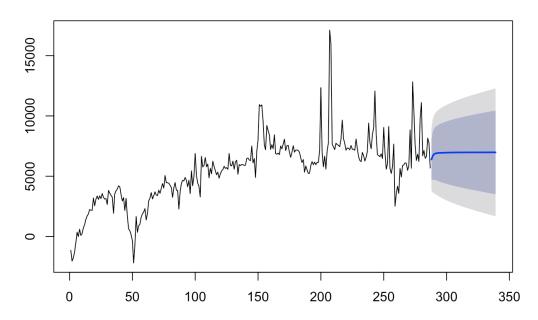






# Forecast Auto ARIMA
auto.total.social.media.forecast <- forecast(auto.total.social.media, h=52)
plot(auto.total.social.media.forecast)</pre>

#### Forecasts from ARIMA(2,1,2)

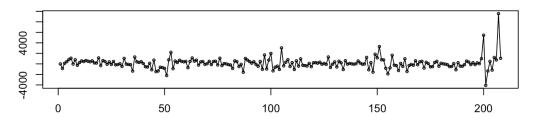


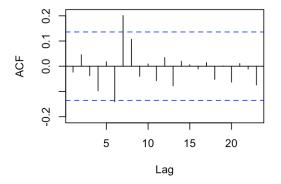
```
# Train and Test Split
clem_train_social_data_arima <- clem_data_social_ts[1:208,8]
head(clem_train_social_data_arima)</pre>
```

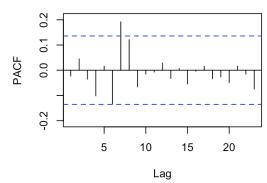
```
## [1] -1131.2220 -2036.4831 -1766.2691 -1284.4013 -523.6249 365.9977
```

```
# Choosing Model 13 - ARIMA(1,1,1,0,0,0)
clem_train_social_arima_model <- Arima(clem_train_social_data_arima, order=c(1,1,1))
tsdisplay(residuals(clem_train_social_arima_model))</pre>
```

#### residuals(clem\_train\_social\_arima\_model)





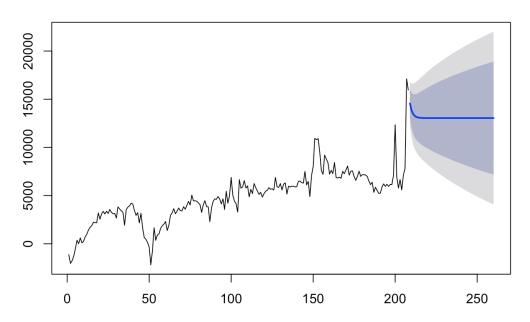


## # Forecasting forecast.clem.social.arima <- forecast(clem\_train\_social\_arima\_model, h=52) forecast.clem.social.arima\$mean</pre>

```
## Time Series:
## Start = 209
## End = 260
## Frequency = 1
## [1] 14564.48 13837.09 13457.46 13259.34 13155.94 13101.97 13073.81
## [8] 13059.11 13051.44 13047.43 13045.34 13044.25 13043.68 13043.39
## [15] 13043.23 13043.15 13043.11 13043.09 13043.07 13043.07 13043.07
## [22] 13043.06 13043.06 13043.06 13043.06 13043.06 13043.06 13043.06
## [29] 13043.06 13043.06 13043.06 13043.06 13043.06 13043.06 13043.06
## [43] 13043.06 13043.06 13043.06 13043.06 13043.06 13043.06
## [43] 13043.06 13043.06 13043.06 13043.06 13043.06 13043.06
## [50] 13043.06 13043.06 13043.06
```

```
# Plot
plot(forecast(object=forecast.clem.social.arima,h="52"))
```

#### Forecasts from ARIMA(1,1,1)



```
ARIMA for Clementine Sales Volume
 # Clementines Sales Volume
 f1<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,0,0,0,0,0,0)
 f2<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,0,1,0,0,0)
 f3<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,0,2,0,0,0)
 ## Warning in arima(y, order = c(p, d, q), seasonal = list(order = c(P, D, :
 ## possible convergence problem: optim gave code = 1
 ## Warning in arima(y, order = c(p, d, q), seasonal = list(order = c(P, D, :
 ## possible convergence problem: optim gave code = 1
 f4<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,1,1,0,0,0)
 ## Warning in log(s2): NaNs produced
 f5<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,1,2,0,0,0)
 ## Warning in arima(y, order = c(p, d, q), seasonal = list(order = c(P, D, :
 ## possible convergence problem: optim gave code = 1
 ## Warning in arima(y, order = c(p, d, q), seasonal = list(order = c(P, D, :
 ## possible convergence problem: optim gave code = 1
 ## Warning in arima(y, order = c(p, d, q), seasonal = list(order = c(P, D, :
 ## possible convergence problem: optim gave code = 1
```

```
f6<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,1,0,0,0,0)
f7<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,2,0,0,0,0)
f8<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,2,1,0,0,0)
f9<- fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 2,2,2,0,0,0)
## Warning in log(s2): NaNs produced
f10<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,0,0,0,0,0)
f11<-fun.illustrate.2(clem data sales ts$salestszSeasonallyAdjusted,52, 1,0,1,0,0,0)
f12<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,0,2,0,0,0)
f13<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,1,1,0,0,0)
f14<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,1,2,0,0,0)
f15<-fun.illustrate.2(clem data sales ts$salestszSeasonallyAdjusted,52, 1,1,0,0,0,0)
f16<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,2,0,0,0,0)
f17<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,2,1,0,0,0)
f18<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 1,2,2,0,0,0)
f19<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,0,0,0,0,0,0)
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
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## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
```

```
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
f20<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,0,1,0,0,0)
f21<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,0,2,0,0,0)
f22<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,1,0,0,0,0)
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
## Warning in cor(pred$pred, yvec.hold): the standard deviation is zero
```

```
f24<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,1,2,0,0,0)
f25<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,2,0,0,0,0)
f26<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,2,1,0,0,0)
f27<-fun.illustrate.2(clem_data_sales_ts$salestszSeasonallyAdjusted,52, 0,2,2,0,0,0)
```

#### # Concatenate

total.sales.volume <- c(f1\$Average, f2\$Average, f3\$Average, f4\$Average, f5\$Average, f6\$Average, f7\$Average, f8\$Average,f9\$Average,f10\$Average,f11\$Average,f12\$Average,f13\$Average,f14\$Average,f15\$Average,f16\$Ave rage, f17\$Average, f18\$Average, f19\$Average, f20\$Average, f21\$Average, f22\$Average, f23\$Average, f24\$Averag e, f25\$Average, f26\$Average, f27\$Average)

#### # Minimum

summary(total.sales.volume)

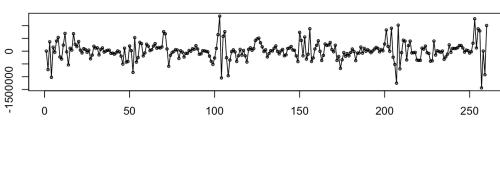
```
Min.
               1st Qu.
                          Median
                                       Mean
                                              3rd Qu.
                                                            Max.
## 1.343e+12 1.404e+12 1.411e+12 5.285e+12 1.873e+12 7.704e+13
```

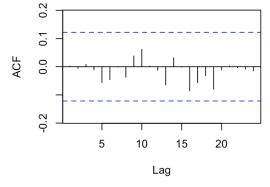
which.min(total.sales.volume)

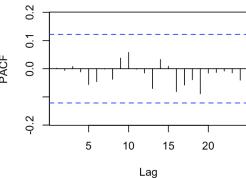
```
## [1] 17
```

```
# Auto ARIMA (3,1,0)
auto.sales.volume <- auto.arima(clem_data_sales_ts$salestszSeasonallyAdjusted)</pre>
tsdisplay(residuals(auto.sales.volume))
```

#### residuals(auto.sales.volume)

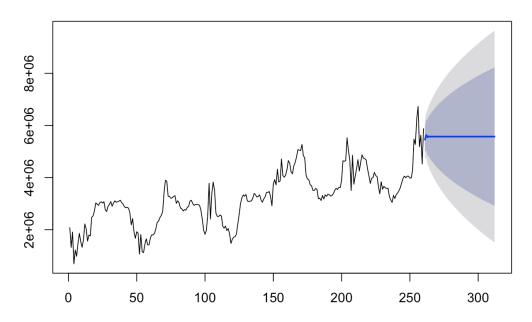






# Forecast Auto ARIMA auto.sales.volume.forecast <- forecast(auto.sales.volume, h=52)</pre> plot(auto.sales.volume.forecast)

#### Forecasts from ARIMA(3,1,0)

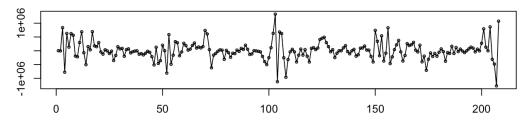


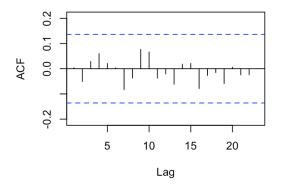
```
# Train and Test Split
clem_train_sales_data_arima <- clem_data_sales_ts[1:208,2]
head(clem_train_sales_data_arima)</pre>
```

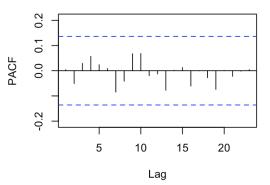
```
## [1] 2077991.2 1320663.6 1909651.8 689723.6 1220800.4 979856.2
```

```
# Choosing Model 17 - ARIMA(1,2,1,0,0,0)
clem_train_sales_arima_model <- Arima(clem_train_sales_data_arima, order=c(1,2,1))
tsdisplay(residuals(clem_train_sales_arima_model))</pre>
```

#### residuals(clem\_train\_sales\_arima\_model)





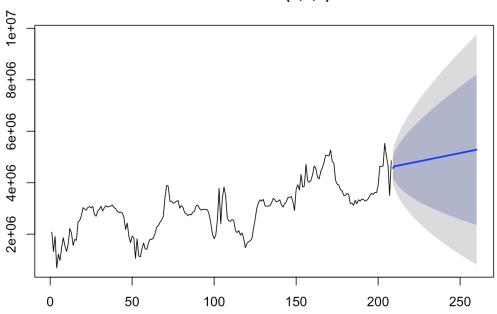


```
# Forecasting
forecast.clem.sales.arima <- forecast(clem_train_sales_arima_model, h=52)
forecast.clem.sales.arima$mean</pre>
```

```
## Time Series:
## Start = 209
## End = 260
## Frequency = 1
## [1] 4569266 4647909 4646237 4662379 4674570 4687638 4700511 4713427
## [9] 4726333 4739242 4752150 4765058 4777966 4790874 4803783 4816691
## [17] 4829599 4842507 4855415 4868324 4881232 4894140 4907048 4919956
## [25] 4932865 4945773 4958681 4971589 4984497 4997406 5010314 5023222
## [33] 5036130 5049038 5061947 5074855 5087763 5100671 5113579 5126488
## [41] 5139396 5152304 5165212 5178121 5191029 5203937 5216845 5229753
## [49] 5242662 5255570 5268478 5281386
```

```
# Plot
plot(forecast(object=forecast.clem.sales.arima,h="52"))
```

#### Forecasts from ARIMA(1,2,1)



Both time series, clementine sales volume and social media are of I(1) OR > 1 process, therefore the series is not stationary and has a trend and drift, and is not showing a tendency to return back to mean.

Step 1: Check if the series is stationary.

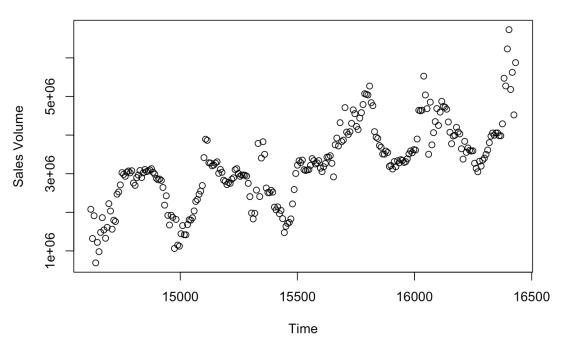
```
sales.volume <- clem_data_sales_ts$salestszSeasonallyAdjusted
#d.sales.volume <- diff(sales.volume)
week <- clem_data_sales_ts$Date

# Descriptive statistics and plotting the data
summary(sales.volume)</pre>
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 689700 2639000 3219000 3229000 3865000 6730000
```

```
#summary(d.sales.volume)
plot.ts(week, sales.volume, main = "Clementine sales volume", xlab = "Time", ylab = "Sales Volume")
```

#### Clementine sales volume



```
#Based on the sales volume time series, there appears to be a linear trend.
#Therefore, for stationarity test we include a trend element in augmented dickey fuller test.
#Augmented Dickey Fuller test for stationarity
# Sales Volume
# Null hypothesis HO: Non - Stationary
#library(urca)
#summary(ur.df(y=sales.volume, lags = 52, type = "trend"))
adf.test(sales.volume, alternative = "stationary")
   Augmented Dickey-Fuller Test
## data: sales.volume
## Dickey-Fuller = -3.2802, Lag order = 6, p-value = 0.07494
## alternative hypothesis: stationary
# Null hypothesis: Series is stationary around a constant mean
# Alternative: Series is non stationary
kpss.test(sales.volume, null = "Trend")
## Warning in kpss.test(sales.volume, null = "Trend"): p-value greater than
## printed p-value
```

```
##
## KPSS Test for Trend Stationarity
##
## data: sales.volume
## KPSS Trend = 0.1167, Truncation lag parameter = 3, p-value = 0.1
```

ADF Test: With the p-value of 0.07, greater than significance level of 0.05 suggests that we fail reject the null hypothesis that the series is not stationary and unit root. In other words, we have no evidence that the series is stationary.

KPSS Test: At significance level of 5% or p-value > 0.05, we reject the 'Trend' null hypothesis that the series is stationary with a linear trend. In other words, we have no evidence that the series is stationary.

```
clem_total_social_media <- clem_data_social_ts$Total.social.media

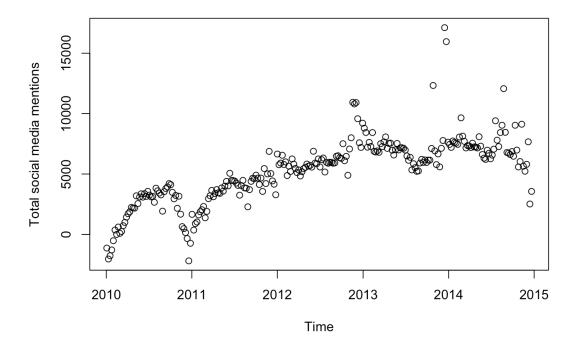
#d.clem_blogs <- diff(clem_blogs)
week <- clem_data_social_ts$Analysis_Date

# Descriptive statistics and plotting the data
summary(clem_total_social_media)</pre>
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## -2191 3556 5772 5276 7020 17110
```

plot(week, clem\_total\_social\_media, main = "Clementine Total Social media mentions", xlab = "Time", ylab =
"Total social media mentions")

#### **Clementine Total Social media mentions**



```
# Augmented Dickey Fuller test for stationarity
adf.test(clem_total_social_media, alternative = "stationary")
```

```
##
## Augmented Dickey-Fuller Test
##
## data: clem_total_social_media
## Dickey-Fuller = -2.3232, Lag order = 6, p-value = 0.4398
## alternative hypothesis: stationary
```

```
# KPSS test
# Null hypothesis: Series is stationary.
# Alternative: Series is non stationary
kpss.test(clem_total_social_media, null = "Level")
```

```
## Warning in kpss.test(clem_total_social_media, null = "Level"): p-value
## smaller than printed p-value
```

```
##
## KPSS Test for Level Stationarity
##
## data: clem_total_social_media
## KPSS Level = 4.7557, Truncation lag parameter = 3, p-value = 0.01
```

```
\# Low p-value suggests that the series is Non - Stationary. We reject the null hypothesis of stationarity.
```

Small p-value of 0.01, less than significance level of 0.05 suggests that we reject the null hypothesis that the series is stationary.

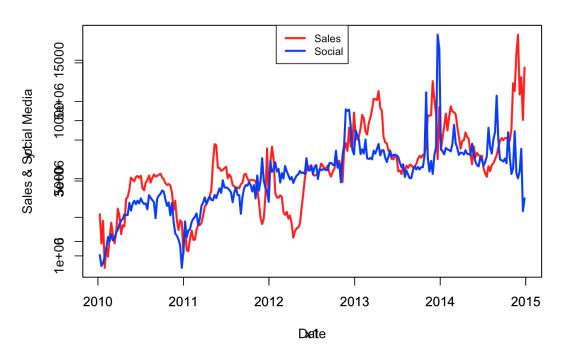
Now that we have established both series are not stationary and has a trend or drift component, and are of I(1) or > process, we perform Johansen test for cointegration.

```
# Plot Sales and Sum Social Media Mentions

x1 <- clem_data_sales_ts$Date
y1 <- sales.volume
y2 <- clem_total_social_media

plot( x1, y1, type="1", col="red", main = "Clementines", xlab = "Date", lwd = "2.5")
par(new=TRUE)
plot( x1, y2, type="1", col="blue", ylab = "Sales & Social Media", lwd = "2.5")
legend("top", legend=c("Sales", "Social"), col=c("red", "blue"), lwd = 2.5, cex=0.8)</pre>
```

#### Clementines



```
library("urca")
co.test.matrix <- cbind(sales.volume, clem_total_social_media)
CoIntegrationTest =ca.jo(co.test.matrix,type="trace",K=4,ecdet="none", spec="longrun")
summary(CoIntegrationTest)</pre>
```

```
##
## ####################
## # Johansen-Procedure #
  ########################
##
##
##
   Test type: trace statistic , with linear trend
##
## Eigenvalues (lambda):
##
  [1] 0.05653831 0.03226990
  Values of teststatistic and critical values of test:
##
##
            test 10pct 5pct 1pct
  r <= 1 | 8.4 6.50 8.18 11.65
  r = 0 \mid 23.3 \mid 15.66 \mid 17.95 \mid 23.52
##
## Eigenvectors, normalised to first column:
  (These are the cointegration relations)
##
##
                               sales.volume.14 clem_total_social_media.14
## sales.volume.14
                                        1.0000
                                                                    1.0000
                                     -432.5455
                                                                  149.9026
##
  clem_total_social_media.14
##
## Weights W:
   (This is the loading matrix)
##
##
                              sales.volume.14 clem_total_social_media.14
                                                            -0.0292266540
## sales.volume.d
                                -0.0965732245
                                 0.0002522272
                                                            -0.0001353827
## clem_total_social_media.d
```

With lag of k=4, we see that our test statistic ( $r \le 1$ ) of 8.4 is higher than at least one of # the critical values at 10% confidence level 6.50, we can assume there is cointegration of r time series.

# http://denizstij.blogspot.com/2013/11/cointegration-tests-adf-and-johansen.html (http://denizstij.blogspot.com/2013/11/cointegration-tests-adf-and-johansen.html)

Running VAR model for Multivariate time series.

Multivariate time series analysis is used when one wants to model and explain the interactions and comovements among a group of time series variables

 http://faculty.washington.edu/ezivot/econ584/notes/multivariatetimeseries.pdf (http://faculty.washington.edu/ezivot/econ584/notes/multivariatetimeseries.pdf)

Granger Causality One of the main uses of VAR models is forecasting.

The following intuitive notion of a variable's forecasting ability is due to Granger (1969).

• If a variable, or group of variables, y1 (social media mentions) is found to be helpful for predicting another variable (sales volume), or group of variables, y2 then y1 is said to Granger-cause y2; otherwise it is said to fail to Granger-cause y2.

VAR Model Building and Evaluation steps:

- 1. Split Raw Clem sales and social data into train and validation (1 year).
- 2. Based on the # of observation split the ARIMA values into train and validation (1 year).
- 3. Run the VAR model on training set and forecast sales, social and measure the prediction accuracy by comparing the validation set.
- 4. Make plots of sales, social and arima (benchmark)
- 5. Run the model on validation set.
- 6. Make plots of sales, social and arima (benchmark)
- 7. Calculate the difference / lift / between sales arima forecasts and sales forecasts from var model.

```
library(vars)
```

```
## Loading required package: MASS
## Loading required package: strucchange
## Loading required package: sandwich
## Loading required package: lmtest
```

#### library(astsa)

```
##
## Attaching package: 'astsa'
##
## The following object is masked from 'package:forecast':
##
## gas
```

```
# Read Clementine Google Trends data in for exogenous variable in VAR model
setwd("/Users/kevalshah/Keval_Backup/University/UChicago/Capstone/Data/Data Clean up/Clean data to be used f
or Analysis")
clem_google_trends <- read.csv("Clem_Google_Trends_Searches.csv")</pre>
# Plot sales, social media and google trends
x1 <- clem_data_sales_ts$Date</pre>
y1 <- clem_data_sales_ts$salestszSeasonallyAdjusted
y2 <- clem_data_social_ts$Total.social.media
y3 <- clem google trends$clementine.Searches
#plot( x1, y1, type="1", col="red", main = "Clementines Sales, Social #Media and Google Trends", xlab = "Dat
e'', 1wd = "2.5")
#par(new=TRUE)
#plot( x1, y2, type="1", col="blue", ylab = "Social", lwd = "2.5")
#par(new=TRUE)
#plot( x1, y3, type="1", col="orange", ylab = "Social & GT", 1wd = "2.5")
#legend("top", legend=c("Sales", "Social"), col=c("red", "blue"), lwd = #2.5, cex=0.8)
# Run VAR Model on Training set
length(clem_data_social_ts$Total.social.media)
```

## [1] 260

length(clem\_data\_sales\_ts\$salestszSeasonallyAdjusted)

## [1] 260

length(clem\_data\_sales\_ts\$Date)

## [1] 260

length(clem\_google\_trends\$clementine.Searches)

## [1] 260

```
Train_clem_sales <- clem_data_sales_ts[1:208,2]
Train_clem_week <- clem_data_sales_ts[1:208,1]
Train_clem_social <- clem_data_social_ts[1:208,8]
Train_clem_google_trends <- clem_google_trends[1:208,3]

# Endogenous variables
Train_VAR_clem <- cbind(Train_clem_sales, Train_clem_social)

#VAR Select
VARselect(Train_VAR_clem, lag.max = 10, type = "both", exogen = cbind(x3 =Train_clem_google_trends))</pre>
```

```
## AIC(n) HQ(n) SC(n) FPE(n)

## 9 1 1 9

##

## $criteria

## AIC(n) 3.942164e+01 3.941067e+01 3.944051e+01 3.944992e+01 3.947104e+01

## HQ(n) 3.948886e+01 3.950478e+01 3.956151e+01 3.959780e+01 3.964581e+01

## SC(n) 3.958771e+01 3.964317e+01 3.973945e+01 3.981528e+01 3.990283e+01

## FPE(n) 1.320110e+17 1.305756e+17 1.345400e+17 1.358253e+17 1.387452e+17

## AIC(n) 3.949217e+01 3.941717e+01 3.939753e+01 3.937395e+01 3.940232e+01

## HQ(n) 3.969384e+01 3.964572e+01 3.965297e+01 3.965628e+01 3.971153e+01

## SC(n) 3.999039e+01 3.998182e+01 4.002861e+01 4.007146e+01 4.016626e+01

## FPE(n) 1.417376e+17 1.315308e+17 1.290163e+17 1.260623e+17 1.297549e+17
```

Train\_VAR\_model\_clem <- VAR(Train\_VAR\_clem, p=2, type="both", exogen = cbind(x3 =Train\_clem\_google\_trends))
summary(Train\_VAR\_model\_clem)</pre>

```
##
## VAR Estimation Results:
## =========
## Endogenous variables: Train_clem_sales, Train_clem_social
## Deterministic variables: both
## Sample size: 206
## Log Likelihood: -4632.721
## Roots of the characteristic polynomial:
## 0.939 0.655 0.1561 0.1561
## Call:
## VAR(y = Train VAR clem, p = 2, type = "both", exogen = cbind(x3 = Train clem google trends))
##
##
## Estimation results for equation Train clem sales:
## Train clem sales = Train clem sales.11 + Train clem social.11 + Train clem sales.12 + Train clem social.1
2 + const + trend + x3
##
##
                       Estimate Std. Error t value Pr(>|t|)
## Train clem sales.l1 7.146e-01 7.059e-02 10.123 < 2e-16 ***
## Train_clem_social.11 6.661e+01 2.102e+01
                                           3.169 0.00177 **
## Train_clem_sales.12 1.345e-01 6.992e-02
                                           1.924 0.05582 .
## Train_clem_social.12 -1.277e+01 2.371e+01 -0.539 0.59072
                       2.486e+05 8.975e+04
                                           2.770 0.00614 **
## trend
                      -3.291e+02 7.294e+02 -0.451 0.65236
                      -7.640e+01 1.197e+03 -0.064 0.94919
## x3
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 327500 on 199 degrees of freedom
## Multiple R-Squared: 0.8824, Adjusted R-squared: 0.8789
## F-statistic: 248.9 on 6 and 199 DF, p-value: < 2.2e-16
##
##
## Estimation results for equation Train_clem_social:
## Train_clem_social = Train_clem_sales.11 + Train_clem_social.11 + Train_clem_sales.12 + Train_clem_social.
12 + const + trend + x3
##
##
                        Estimate Std. Error t value Pr(>|t|)
## Train_clem_sales.l1 -3.122e-04 2.340e-04 -1.334 0.18362
## Train_clem_social.11 6.745e-01 6.968e-02 9.680 < 2e-16 ***
## Train clem sales.12 5.885e-04 2.318e-04 2.539 0.01187 *
## Train clem social.12 5.552e-02 7.860e-02 0.706 0.48075
                      -3.760e+02 2.975e+02 -1.264 0.20778
## const
                       7.356e+00 2.418e+00
## trend
                                           3.042 0.00267 **
                       4.643e+00 3.969e+00
                                           1.170 0.24351
## x3
##
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 1086 on 199 degrees of freedom
## Multiple R-Squared: 0.8437, Adjusted R-squared: 0.839
## F-statistic: 179 on 6 and 199 DF, p-value: < 2.2e-16
##
##
##
## Covariance matrix of residuals:
##
                   Train_clem_sales Train_clem_social
## Train_clem_sales
                        1.073e+11
                                          -29461429
## Train_clem_social
                         -2.946e+07
                                            1178445
##
## Correlation matrix of residuals:
                   Train_clem_sales Train_clem_social
```

```
## Train_clem_sales 1.00000 -0.08287
## Train_clem_social -0.08287 1.00000
```

The adjusted R-Squared of 87% for equation predicting sales as dependent variable and endogenous variables of social media and sales with lag order of 2 and exogenous variable of google trends with constant and trend deterministic variable indicates a good fit. On the other hand, the inverse, of predicting social media with sales as predictors has Adj. R-Squared of 67%.

Now, we fit our training model on our validation set and check the prediction error / accuracy.

```
# Run VAR Model on Validation / Test Set
Test clem sales <- clem data sales ts[209:260,2]
Test_clem_week <- clem_data_sales_ts[209:260,1]</pre>
Test_clem_social <- clem_data_social_ts[209:260,8]</pre>
Test_clem_google_trends <- clem_google_trends[209:260,3]</pre>
length(Test_clem_sales)
## [1] 52
length(Test_clem_week)
## [1] 52
length(Test_clem_social)
## [1] 52
length(Test_clem_google_trends)
## [1] 52
# Endogenous variables
#Test_VAR_clem <- cbind(Test clem sales, Test clem social)</pre>
#VAR Select
#VARselect(Test_VAR_clem, lag.max = 10, type = "both", exogen = cbind(x3 =Test_clem_google_trends))
#Test VAR model clem <- VAR(Test VAR clem, p=7, type="both", exogen = cbind(x3 =Test clem google trends))
#summary(Test_VAR_model_clem)
# Clementine prediction
var_train_forecasts <- predict(Train_VAR_model_clem, n.ahead = 52, ci = 0.95, dumvar = cbind(x3 =Test_clem_g</pre>
oogle_trends))
summary(var_train_forecasts)
##
            Length Class Mode
## fcst
             2
                   -none- list
## endog
            416
                   -none- numeric
## model
             10
                   varest list
## exo.fcst 52
                   -none- numeric
```

head(var\_train\_forecasts)

```
## $fcst
## $fcst$Train_clem_sales
           fcst
                 lower
                          upper
## [1,] 4957466 4315589 5599342 641876.5
## [2,] 5083290 4288474 5878107 794816.4
  [3,] 5165505 4265563 6065447 899942.0
## [4,] 5205713 4224459 6186968 981254.1
## [5,] 5223492 4176771 6270214 1046721.8
## [6,] 5227128 4126110 6328145 1101017.5
## [7,] 5220000 4073232 6366767 1146767.6
## [8,] 5208112 4022412 6393812 1185700.2
## [9,] 5192129 3973075 6411183 1219054.1
## [10,] 5174838 3927070 6422606 1247767.8
## [11,] 5155159 3882580 6427738 1272579.0
## [12,] 5135517 3841435 6429598 1294082.0
## [13,] 5116309 3803546 6429072 1312763.1
## [14,] 5096950 3767924 6425976 1329025.7
## [15,] 5078296 3735088 6421503 1343207.4
## [16,] 5063851 3708259 6419444 1355592.4
## [17,] 5050097 3683675 6416519 1366421.9
## [18,] 5038051 3662149 6413953 1375901.6
## [19,] 5025050 3640843 6409258 1384207.5
## [20,] 5014255 3622765 6405746 1391490.7
## [21,] 5004746 3606864 6402628 1397881.6
## [22,] 4997014 3593521 6400507 1403493.0
## [23,] 4986625 3578202 6395047 1408422.6
## [24,] 4977389 3564634 6390145 1412755.1
## [25,] 4968331 3551767 6384896 1416564.5
## [26,] 4959147 3539232 6379062 1419915.1
## [27,] 4949552 3526689 6372415 1422863.0
## [28,] 4942551 3517093 6368008 1425457.4
## [29,] 4935123 3507382 6362864 1427741.1
## [30,] 4929426 3499674 6359178 1429751.9
## [31,] 4925912 3494390 6357435 1431522.5
## [32,] 4921139 3488057 6354221 1433082.0
## [33,] 4919630 3485174 6354085 1434455.8
## [34,] 4916202 3480536 6351868 1435666.0
## [35,] 4914955 3478223 6351688 1436732.3
## [36,] 4912323 3474651 6349995 1437671.9
## [37,] 4912048 3473548 6350548 1438499.9
## [38,] 4911231 3472001 6350460 1439229.7
## [39,] 4920050 3480177 6359923 1439872.8
## [40,] 4926456 3486016 6366896 1440439.7
## [41,] 4934930 3493991 6375870 1440939.4
## [42,] 4942126 3500746 6383506 1441379.8
## [43,] 4948544 3506776 6390312 1441768.1
## [44,] 4955207 3513096 6397317 1442110.3
## [45,] 4962805 3520393 6405217 1442412.1
## [46,] 4971847 3529169 6414525 1442678.1
## [47,] 4987158 3544245 6430070 1442912.6
## [48,] 5007802 3564683 6450922 1443119.4
## [49,] 5026665 3583364 6469967 1443301.7
## [50,] 5047449 3603987 6490912 1443462.4
## [51,] 5069068 3625464 6512672 1443604.2
## [52,] 5091584 3647855 6535313 1443729.1
##
## $fcst$Train_clem_social
##
            fcst lower
                              upper
## [1,] 13783.91 11656.250 15911.58 2127.663
## [2,] 13026.47 10443.024 15609.91 2583.445
## [3,] 12350.29 9566.001 15134.57 2784.287
## [4,] 11893.97 8991.194 14796.74 2902.774
## [5,] 11587.19 8606.328 14568.05 2980.861
## [6,] 11352.55 8314.280 14390.81 3038.267
   [7,] 11198.58 8115.022 14282.14 3083.557
```

```
##
   [8,] 11074.85 7953.967 14195.74 3120.887
##
   [9,] 10985.08 7832.630 14137.54 3152.454
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######################################	[55,] [56,] [57,] [58,] [59,] [60,] [61,] [62,] [63,] [64,] [65,] [66,] [67,] [68,] [70,] [71,] [72,] [73,] [74,] [75,] [76,] [77,] [78,]	1122230.4 1444634.3 1655096.4 1418642.3 1417775.8 1681882.6 1805371.3 1797987.2 1857040.8 2034920.6 2282016.0 2331639.7 2465413.2 2549572.6 2693755.2 3416675.3 3893915.3 3863239.9 3282693.9 3277275.7 3204178.0 3224071.2 3274183.2 3307544.7	889.7308709 1028.5986594 1610.3751017 1871.9976979 2042.3558709 2314.2741402 1375.0217363 1905.4544286 2959.6827940 3196.8246209 3641.3174094 3116.1755825 3385.9496209 3707.0385632 3443.4568325 3398.9496209 3847.3198132 3583.1202940 3999.3005825 4394.2573132 4020.2693325 5059.0938517 4461.9015440 4460.0361594
#######################################	[55,] [56,] [57,] [58,] [59,] [60,] [61,] [62,] [63,] [64,] [65,] [66,] [67,] [68,] [70,] [71,] [72,] [73,] [74,] [75,] [76,] [77,] [78,] [79,]	1122230.4 1444634.3 1655096.4 1418642.3 1417775.8 1681882.6 1805371.3 1797987.2 1857040.8 2034920.6 2282016.0 2331639.7 2465413.2 2549572.6 2693755.2 3416675.3 3893915.3 3863239.9 3282693.9 3277275.7 3204178.0 3224071.2 3274183.2 3307544.7 3010483.5	889.7308709 1028.5986594 1610.3751017 1871.9976979 2042.3558709 2314.2741402 1375.0217363 1905.4544286 2959.6827940 3196.8246209 3641.3174094 3116.1755825 3385.9496209 3707.0385632 3443.4568325 3398.9496209 3847.3198132 3583.1202940 3999.3005825 4394.2573132 4020.2693325 5059.0938517 4461.9015440 4460.0361594 4417.1856786
######################################	[55,] [56,] [57,] [58,] [59,] [60,] [61,] [62,] [63,] [64,] [65,] [66,] [67,] [68,] [70,] [71,] [72,] [73,] [74,] [75,] [76,] [77,] [78,]	1122230.4 1444634.3 1655096.4 1418642.3 1417775.8 1681882.6 1805371.3 1797987.2 1857040.8 2034920.6 2282016.0 2331639.7 2465413.2 2549572.6 2693755.2 3416675.3 3893915.3 3863239.9 3282693.9 3277275.7 3204178.0 3224071.2 3274183.2 3307544.7	889.7308709 1028.5986594 1610.3751017 1871.9976979 2042.3558709 2314.2741402 1375.0217363 1905.4544286 2959.6827940 3196.8246209 3641.3174094 3116.1755825 3385.9496209 3707.0385632 3443.4568325 3398.9496209 3847.3198132 3583.1202940 3999.3005825 4394.2573132 4020.2693325 5059.0938517 4461.9015440 4460.0361594
#######################################	[55,] [56,] [57,] [58,] [59,] [60,] [61,] [62,] [63,] [64,] [65,] [66,] [67,] [68,] [70,] [71,] [72,] [73,] [74,] [75,] [76,] [77,] [78,] [79,]	1122230.4 1444634.3 1655096.4 1418642.3 1417775.8 1681882.6 1805371.3 1797987.2 1857040.8 2034920.6 2282016.0 2331639.7 2465413.2 2549572.6 2693755.2 3416675.3 3893915.3 3863239.9 3282693.9 3277275.7 3204178.0 3224071.2 3274183.2 3307544.7 3010483.5	889.7308709 1028.5986594 1610.3751017 1871.9976979 2042.3558709 2314.2741402 1375.0217363 1905.4544286 2959.6827940 3196.8246209 3641.3174094 3116.1755825 3385.9496209 3707.0385632 3443.4568325 3398.9496209 3847.3198132 3583.1202940 3999.3005825 4394.2573132 4020.2693325 5059.0938517 4461.9015440 4460.0361594 4417.1856786

1/2010		
## [82,]	2832657.0	3248.4491402
## [83 <b>,</b> ]	2802963.4	4046.7356786
## [84,]	2718567.4	4473.7818325
## [85,]	2772830.2	3851.6626017
## [86,]	2750812.7	3824.9222171
## [87 <b>,</b> ]	2855598.4	2284.0106786
## [88,]	2893680.6	3707.6299094
## [89,]	3102093.2	4395.8914479
## [90 <b>,</b> ]	3128923.4	4657.5087556
## [91,]	3005128.3	4610.6068325
## [92,]	2932257.0	4902.8491402
## [93,]	2965397.8	4659.5395248
## [94,]	2966578.1	4131.5145248
## [95,]	2961161.5	4665.0587555
## [96,]	2936383.4	3560.7683709
## [97,]	2749571.7	5450.6414479
## [98 <b>,</b> ]	2405608.3	4209.1837555
## [99,]	1981605.4	5008.1472171
	1827741.7	6874.3202940
## [101,]	1972377.4	5040.5318325
## [102,]	2575755.0	4428.9587556
## [103,]	3783529.3	4158.2818325
		3281.2202940
## [104,]	2407656.1	
## [105 <b>,</b> ]	3404523.8	6653.7779863
## [106,]	3827436.2	5766.5169286
## [107,]	3501785.9	5904.7308709
## [108,]	2629319.0	6553.5986594
## [109 <b>,</b> ]	2512624.7	5788.3751017
## [110,]	2506626.4	6005.9976979
## [111,]	2569186.5	4871.3558709
## [112,]	2522442.1	5654.2741402
## [113,]	2132970.4	5208.0217363
## [114,]	2061745.6	6248.4544286
## [115,]	2139889.8	5815.6827940
## [116,]	1965566.4	5466.8246209
## [117 <b>,</b> ]	2047397.1	5119.3174094
## [118,]	1834710.0	5334.1755825
## [119,]	1473312.3	4837.9496209
	1637293.6	5191.0385632
## [120,]		
## [121,]	1712948.7	5445.4568325
## [122,]	1736100.5	5549.9496209
## [123,]	1828442.3	5825.3198132
	2217328.1	
		5656.1202940
## [125,]	2589052.4	5709.3005825
## [126 <b>,</b> ]	3005289.8	5573.2573132
## [127,]	3220444.8	6885.2693325
	3335409.4	5905.0938517
## [128,]		
## [129,]	3285071.4	5856.9015440
## [130,]	3352387.0	6249.0361594
## [131,]	3102707.3	5584.1856786
		6188.3760632
## [132,]	3081498.6	
## [133,]	3097255.0	6323.4260632
## [134,]	3104773.8	5165.4491402
## [135,]	3217716.8	5967.7356786
	3391157.8	
## [136,]		5889.7818325
## [137,]	3337973.0	5973.6626017
## [138,]	3251749.7	5961.9222171
## [139,]	3279336.1	5894.0106786
	3337459.8	5919.6299094
## [141,]	3141980.4	6472.8914479
## [142,]	3053319.6	6511.5087555
## [143,]	3178707.0	6347.6068325
_ · · -	3262688.0	6295.8491402
## [145 <b>,</b> ]		7600 6306340
	3428266.8	7508.5395248
## [146,]	3428266.8	6103.5145248

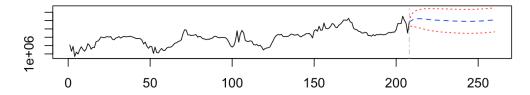
1/2010		
## [147,]	3466194.8	6464.0587555
## [148,]	3268942.3	4895.7683709
## [149,]	2916938.9	7071.6414479
## [150 <b>,</b> ]	3746737.1	7998.1837555
## [151,]	3922153.6	10936.1472171
	3718288.6	10801.3202940
## [153,]	4321226.9	10913.5318325
## [154,]	3830955.8	9575.9587556
## [155 <b>,</b> ]	3868903.8	7584.2818325
## [156,]	4712227.8	7202.2202940
## [157,]	4078340.8	9206.7779863
## [158,]	4014880.9	8796.5169286
## [159,]	4087165.5	8436.7308709
## [160,]	4303987.9	7222.5986594
## [161,]	4651768.6	7620.3751017
## [162,]	4554273.3	7278.9976979
## [163,]	4223135.7	8432.3558709
## [164,]	4143781.8	6872.2741402
## [165 <b>,</b> ]	4439329.0	6822.0217363
## [166,]	4581554.0	6914.4544286
## [167,]	4790849.7	6794.6827940
## [168,]	5071836.4	7509.8246209
## [169,]	5056321.8	7271.3174094
	5039456.1	7660.1755825
## [171 <b>,</b> ]	5269521.9	8070.9496209
## [172,]	4839400.7	7125.0385632
## [173,]	4761428.7	7533.4568325
## [174 <b>,</b> ]	4089047.1	7558.9496209
## [175,]	3946073.5	6970.3198132
## [176,]	3912808.2	6573.1202940
## [177 <b>,</b> ]	3727163.8	7007.3005825
## [178,]	3684843.5	7528.2573132
		6994.2693325
## [179,]	3508703.5	
## [180 <b>,</b> ]	3505929.6	7168.0938517
## [181,]	3585424.6	7172.9015440
## [182,]	3549844.9	7131.0361594
## [183,]	3188808.8	6982.1856786
## [184,]	3213007.1	6497.3760632
## [185,]	3120410.0	6138.4260632
## [186,]	3313654.9	6380.4491402
## [187,]	3180083.5	5339.7356786
## [188,]	3336044.6	5852.7818325
## [189,]	3279727.8	5526.6626017
## [190 <b>,</b> ]	3362907.8	5225.9222171
## [191,]	3343593.6	5256.0106786
## [192 <b>,</b> ]	3291203.4	5909.6299094
## [193,]	3311678.7	6214.8914479
## [194,]	3385868.4	5959.5087556
## [195,]	3511870.9	6165.6068325
## [196,]	3589654.9	5956.8491402
## [197,]	3543135.9	6154.5395248
## [198,]	3623337.3	6146.5145248
## [199 <b>,</b> ]	3612042.2	7113.0587555
## [200,]	3898106.6	12330.7683709
## [201,]	4643754.5	6915.6414479
## [202,]	4627300.3	5778.1837555
## [203,]	4645862.9	6663.1472171
## [204,]	5525928.9	5588.3202940
## [205,]	5039683.8	7129.5318325
## [206,]	4683987.3	7772.9587555
## [207,]	3503620.6	17114.2818325
## [208,]	4852728.4	15958.2202940
##		
## \$model		
TH VIIIOUEL		
##		

```
## VAR Estimation Results:
## =========
##
## Estimated coefficients for equation Train_clem_sales:
## Train_clem_sales = Train_clem_sales.ll + Train_clem_social.ll + Train_clem_sales.l2 + Train_clem_social.l
2 + const + trend + x3
##
   Train_clem_sales.11 Train_clem_social.11 Train_clem_sales.12
                      6.661391e+01
##
         7.146392e-01
                                              1.344991e-01
## Train_clem_social.12
                                                      trend
                                  const
##
        -1.277255e+01
                           2.485746e+05
                                              -3.290917e+02
##
##
        -7.639602e+01
##
##
## Estimated coefficients for equation Train clem social:
## Call:
## Train_clem_social = Train_clem_sales.11 + Train_clem_social.11 + Train_clem_sales.12 + Train_clem_social.
12 + const + trend + x3
##
   Train_clem_sales.11 Train_clem_social.11 Train_clem_sales.12
##
        -3.122388e-04
                            6.744784e-01
                                               5.885164e-04
## Train_clem_social.12
                                   const
                                                      trend
##
         5.552320e-02
                           -3.759710e+02
                                               7.355501e+00
##
                  x3
         4.642846e+00
##
##
##
##
## $exo.fcst
##
       x3
## [1,] 78
## [2,] 79
## [3,] 63
## [4,] 60
## [5,] 59
## [6,] 53
## [7,] 54
## [8,] 50
## [9,] 49
## [10,] 43
## [11,] 43
## [12,] 42
## [13,] 39
## [14,] 40
## [15,] 48
## [16,] 44
## [17,] 43
## [18,] 37
## [19,] 41
## [20,] 41
## [21,] 40
## [22,] 29
## [23,] 31
## [24,] 29
## [25,] 26
## [26,] 24
## [27,] 29
## [28,] 25
## [29,] 28
## [30,] 30
## [31,] 24
```

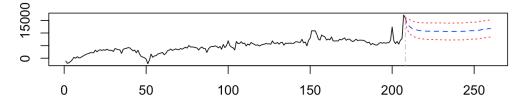
```
## [32,] 30
## [33,] 22
## [34,] 26
## [35,] 21
## [36,] 27
## [37,] 28
## [38,] 51
## [39,] 37
## [40,] 39
## [41,] 33
## [42,] 31
## [43,] 33
## [44,] 37
## [45,] 44
## [46,] 62
## [47,] 70
  [48,] 60
## [49,] 65
## [50,] 67
## [51,] 68
## [52,] 63
```

plot(var\_train\_forecasts, type = "l", main = "Clem sales + social forecast using train model on test set")

#### Clem sales + social forecast using train model on test set



#### Clem sales + social forecast using train model on test set



```
# Check accuracy of our forecasts using train model on test data
# Clem sales volume forecast
accuracy(var_train_forecasts\fcst\forecasts\fcst\forecasts\fcst\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\forecasts\for
```

```
## ME RMSE MAE MPE MAPE
## Test set -850438.1 1135944 1054108 -23.93629 27.29017
```

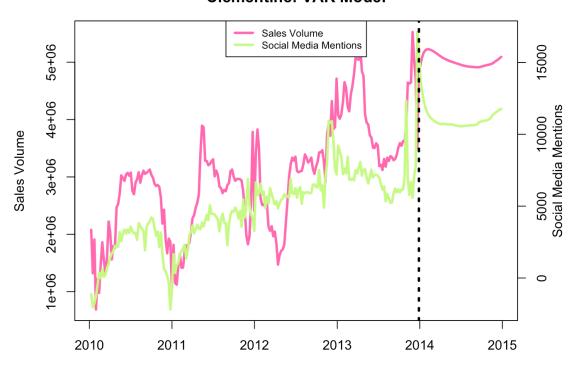
```
# Clem social media forecast
accuracy(var_train_forecasts$fcst$Train_clem_social[,1], Test_clem_social)
```

```
## ME RMSE MAE MPE MAPE
## Test set -3820.709 4162.057 3875.811 -61.91988 62.37655
```

#### Plot Raw Sales and Social media with Forecasts

```
# Append raw + forecast
clem.sales.VAR.All <- append(Train_clem_sales, var_train_forecasts$fcst$Train_clem_sales[,1])</pre>
clem.social.VAR.All <- append(Train_clem_social, var_train_forecasts$fcst$Train_clem_social[,1])</pre>
clem.week.All <- append(Train_clem_week, Test_clem_week)</pre>
clem_df_total <- data.frame(clem.week.All, clem.sales.VAR.All, clem.social.VAR.All)</pre>
mar.default <- c(3,3,3,3) + 0.1
par(mar = mar.default + c(0, 1, 0, 0))
plot(clem_df_total[,1:2], type="1",
     ylab="Sales Volume", xlab="Time (Year)",
     lwd=3, main="Clementine: VAR Model", col="hotpink")
par(new=TRUE)
plot(clem_df_total[,3], type="l", col="darkolivegreen1", axes=FALSE,
     ylab="", xlab="", lwd=3)
axis(4)
mtext("Social Media Mentions", side=4, line=+2, adj=0.5)
abline(v=208, lty=3, lwd=3)
legend("top", legend=c("Sales Volume", "Social Media Mentions"),
       col=c("hotpink","darkolivegreen1"), lwd=3, cex=0.75)
```

#### Clementine: VAR Model



Comparing sales prediction to ARIMA benchmark, make plots and calculate lift

```
## Test_week AR VAR ACTUAL

## 1 2014-01-04 4569266 4957466 3746226

## 2 2014-01-11 4647909 5083290 4060837

## 3 2014-01-18 4646237 5165505 4348938

## 4 2014-01-25 4662379 5205713 4687070

## 5 2014-02-01 4674570 5223492 4250070

## 6 2014-02-08 4687638 5227128 4595462

# Calculate the RMSE. Predicted - Actual values.

AR.error <- forecast.clem.sales.arima$mean - Test_clem_sales
```

```
# Calculate the RMSE. Predicted - Actual Values.

AR.error <- forecast.clem.sales.arima$mean - Test_clem_sales
ar.clem.sales.rmse <- sqrt(mean(AR.error^2))

# Calculate MAE
ar.clem.sales.mae <- mean(abs(AR.error))

# Calculate the RMSE. Predicted - Actual values.

VAR.error <- var_train_forecasts$fcst$Train_clem_sales[,1] - Test_clem_sales
var.clem.sales.rmse <- sqrt(mean(VAR.error^2))

# Calculate MAE
var.clem.sales.mae <- mean(abs(VAR.error))

# Calculate Lift in prediction accuracy
paste(round((((ar.clem.sales.rmse - var.clem.sales.rmse)/ar.clem.sales.rmse))*100, digits = 2), "%", sep =
"")
```

```
## [1] "-4.96%"
```

```
paste(round((((ar.clem.sales.mae - var.clem.sales.mae)/ar.clem.sales.mae))*100, digits = 2), "%", sep = "")
```

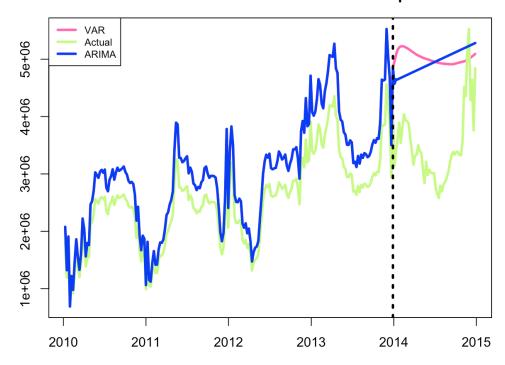
```
## [1] "-12.78%"
```

```
# Create a table to compare RMSE and MAE
accuracy_table <- matrix(c(1082234,790863.8,"26.92%",934652.2,672441,"28.05%"),ncol=3,byrow=TRUE)
colnames(accuracy_table) <- c("ARIMA","VAR", "Lift in Prediction accuracy")
rownames(accuracy_table) <- c("RMSE","MAE")
accuracy_table</pre>
```

```
## ARIMA VAR Lift in Prediction accuracy
## RMSE "1082234" "790863.8" "26.92%"
## MAE "934652.2" "672441" "28.05%"
```

```
# Append ARIMA sales data and forecasts
clem.sales.arima.All <- append(clem_train_sales_data_arima, forecast.clem.sales.arima$mean)</pre>
clem.sales.actual.All <- append(Train_clem_sales, Test_clem_sales)</pre>
# Create a dataframe w Raw sales data, VAR Forecasts, ARIMA Forecasts and
# Test data.
clem_df_total_final <- cbind.data.frame(clem.week.All, clem.sales.VAR.All, clem.sales.actual.All, clem.sale</pre>
s.arima.All)
mar.default <-c(3,3,3,3)+0.1
par(mar = mar.default + c(0, 1, 0, 0))
plot(clem_df_total_final[,1:2], type="1",
     ylab="", xlab="Time (Year)",
     lwd=3, main="Clementine Sales Volume Forecasts Comparison", col="hotpink")
par(new=TRUE)
# Actual data train + test
plot(clem_df_total_final[,3], type="l", col="darkolivegreen1", axes=FALSE,
     ylab="", xlab="", lwd=3)
par(new=TRUE)
# ARIMA Forecast
plot(clem_df_total_final[,4], type="1", col="blue", axes=FALSE,
     ylab="", xlab="", lwd=3)
abline(v=208, lty=3, lwd=3)
legend("topleft", legend=c("VAR", "Actual", "ARIMA"),
       col=c("hotpink","darkolivegreen1","blue"), lwd=3, cex=0.75)
```

#### **Clementine Sales Volume Forecasts Comparison**



Based on the above plot we can see that VAR model which includes social media and lagged sales volume as endogenours predictors and google trends as exogenous variables does predict better than ARIMA model series predicting itself.

```
print(accuracy_table)
```

```
## ARIMA VAR Lift in Prediction accuracy
## RMSE "1082234" "790863.8" "26.92%"
## MAE "934652.2" "672441" "28.05%"
```

Based on Root mean squared error and Mean Absolute Error which calculates the prediction error (predicted - actual), from our train and test split, we see increased accuracy of more than 25% when using VAR models.