University of Houston

Northern Napa Valley Winery, Inc

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Business Modeling for Competitive Advantage: BZAN 7320

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Summary:

Frame the problem you are analyzing, including the answers to the first question:

Two main questions are being asked of the case study. The first being, how many cases of juice will be available to sell to Transcontinental. The second, a production plan for Northern Napa Valley Winery. To estimate how many cases of juice will be available to sell, the production plan must be outlined. To form a production plan, a forecast of sales for the next twelve months (October 2008 – September 2009) must be made utilizing previous sales figures. Additionally, the actual number of available cases of juice must be provided to calculate how many can be sold following the projected sales for the next twelve months. Lastly, the profit made from selling the cases of juice and cases of wine to estimate the economic cost/value to Northern Napa Valley Winery.

Briefly describe the model(s) you used for your analysis:

There were three models utilized in the analysis of Northern Napa Valley Winery's sales. The first being a simple exponential smoothing model, which took into account only an alpha or smoothing parameter. The second model was a Holt forecast, which took into account both an alpha parameter and beta, which represented any trend found within the sales data. Lastly, two Holt-Winters models were utilized, one optimized and the other with manual inputs for alpha, beta, and gamma. The Holt-Winters model takes into account both trend and seasonality in its forecast.

State your conclusions/ recommendations:

Our recommendation is to utilize an optimized holt-winters time series forecast to appropriately take into account trend and seasonality. Provided that 240,000 cases of juice are available and an estimated sales forecast of 195,525 cases of wine over the next twelve months, Northern Napa would have 44,475 cases of juice available to sell to Transcontinental. Provided that each case of juice is sold for $100 a case, the economic impact for Northern Napa Valley Winery would be revenue of 4,447,500.

Analysis:

Describe which models you developed for the annual and monthly forecasts. You should also include any plots or graphs of the data that you made:

Models:

SES Model: A simple exponential smoothing model was one of the four models used in the analysis. Using only an alpha, this model forecasts the positive trend found in the historical sales data without accounting for trend or seasonality.

Holt Model: A Holt model was one of the four models utilized for this analysis. The Holt model, a linear exponential smoothing model, utilizes two parameters, alpha, and beta. These parameters take into account smoothing as well as trends in the time series data.

Holt-Winters: Holt-Winters model was used in the final two models of the analysis. The Holt-Winters model, utilizing alpha, beta, and gamma, takes into account both trend and seasonality in its forecast.

Graphs:

Scatter Plot: A scatter plot graph of Wine Sales (October 2000 – October 2008) was utilized in this analysis. This outlined the trend and seasonality of the data along with any obvious outliers of data points.

Time Series Graph: This graph plotted the time series of the data beginning from October 2000 to October 2008. It was utilized to clearly represent the shifts in wine sales over the years to indicate whether there are identifiable trends or seasonality.

Residual Error Graphs: Graphs plotting the residual errors of each model were utilized in the analysis. This graph demonstrated the residual value found from subtracting the forecasted sales from the actual sales data. This highlighted how the forecast deviated from the actual data.

Summarize the results of at least 2 different models for each forecast in a table that includes all important parameters and measures of accuracy:

Model	Forecast Accuracy					Smoothing Parameters
	AIC	RMSE	MAPE	MAD	MSE	
Simple Exponential	1955.2	2959.2	18.3%	2076.8	8756993.8	α= 0.399
Holt Exponential	1659.4	533.9	18.44%	1978.1	87556993.8	α=0.314, β= 0.001
Winter's Exponential	1656.7	534.7	3.19%	2521.5	285973.4	α= 0.282, β=0.01, Γ=0.001
Optimized Exponential	1665.9	558.4	3.39%	2508.0	311809.4	α=0.1437, β=0.0046, Γ=1e-04

Provide your answers to questions 4 and 5:

Question 4:

Yes, the future forecasts are reasonable as they follow the trend and seasonality of the historical sales data found within the "Exhibit 1" excel file. Through comparing numerous models, the chosen Holt-Winters forecast presents the best measures of forecast accuracy in addition to the lowest error values.

Question 5:

Production Plan (Cases of Wine):

October-2008	17288.10
November-2008	21360.18
December-2008	24616.60
January-2009	14499.73
February-2009	13891.57
March-2009	14889.62
April-2009	15100.57
May-2009	15491.37
June-2009	15608.82
July-2009	14795.42
August-2009	11709.48
September-2009	16273.87
12 – Month Total	**195525.3**

Assumptions such as a positive sales trend and consistent seasonality period over period are two ways in which the forecast's results could be vulnerable to change. Other miscellaneous assumptions include unforeseen weather/climate changes that affect grape yield and economic downturns that in turn reduce/change social discretionary spending.

Recommendation:

Clearly state your recommendation(s) for what the manager should do based on your answer to question 6:

Given historical monthly wine sales from 2000 to 2008, the forecasted demand for the period of October 2008 through September 2009 is 195,525 cases.

Based on this forecasted demand and estimated total production of 240,000 cases of juice, Northern Napa Valley Winery will have 44,475 available cases to sell to Transcontinental or another buyer. To track the success of this sales forecast during the 2008 grape harvest year, the manager should compare actual sales with forecasted sales each month and check for variances. Variances exceeding a 10% threshold are deemed unfavorable and the forecast would need to be reevaluated if unfavorable variances occur each month.

Provide an economic evaluation of your recommendation, if applicable:

At an assumed selling price of $100 per case, the forecasted economic impact of selling the 44,475 excess cases of juice to Transcontinental or another buyer is estimated gross revenue of $4,447,500. Assuming a total cost of $25 per case of juice, the cost for 44,475 cases is calculated at $1,111,875. Therefore, the net profit of selling the excess cases of juice to Transcontinental or another buyer is $3,335,625.

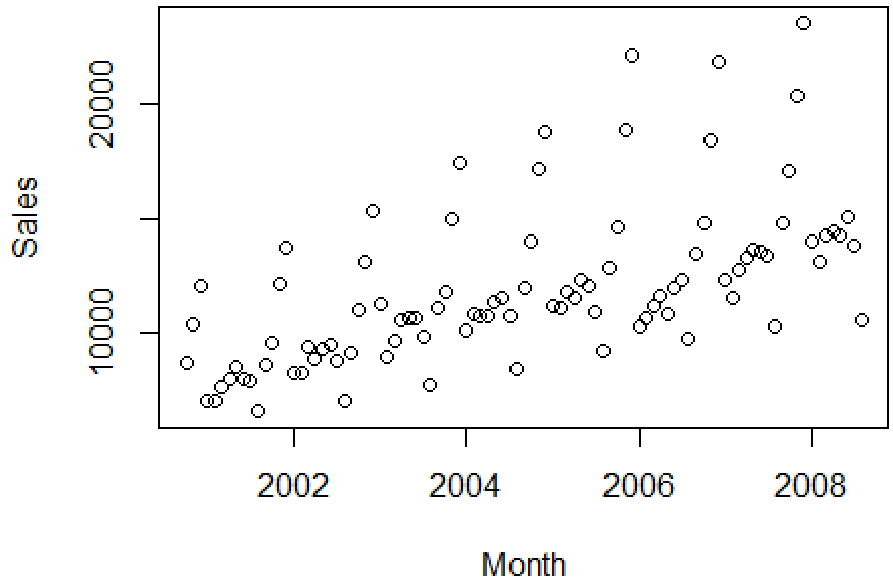
Appendix:

#Case Study BZAN - 7320

Step 1: Data Manipulation

Sales Data

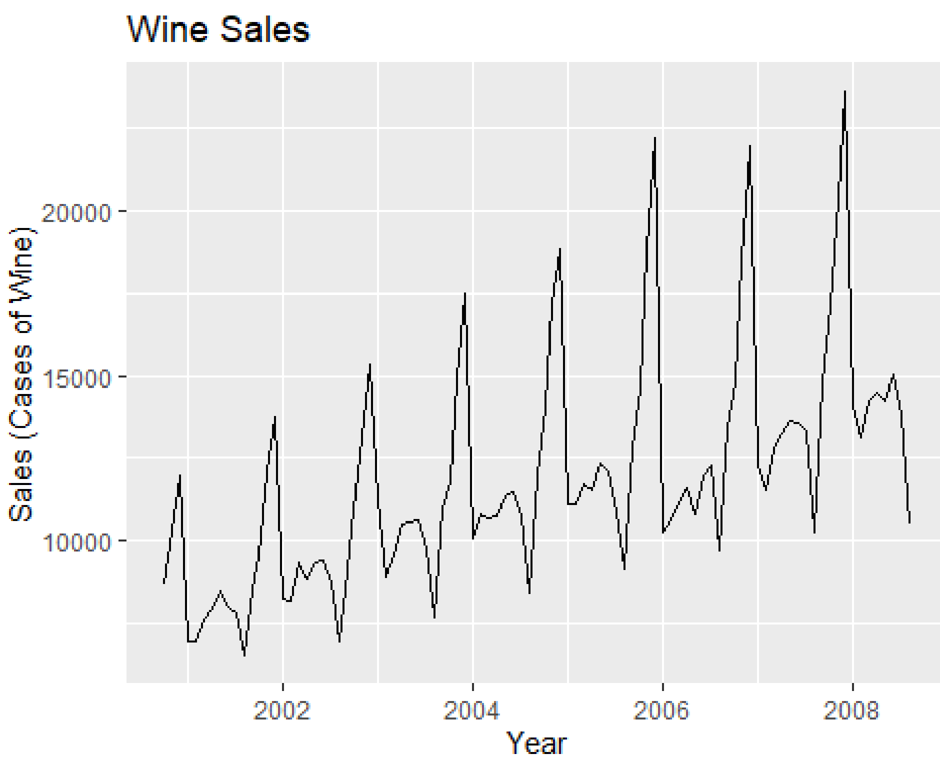
```
library(car)
library(dplyr)
library(tidyverse)
library(readxl)
library(psych)
library(caret)
library(tidyverse)
library(fpp2)
library(forecast)
library(lubridate)
library(knitr)
library(rmarkdown)
library(readxl)
library(DescTools)
library(scales)

data <- read_excel("Final.CaseStudy1.xlsx")
plot(data)
```



I chose data from October 2000 for two reasons. 1) Grape harvest year starts from October to September. 2) Sales in December is much higher than any other month. So, I considered sales of that month as an outlier and since outlier affects any forecasting model, I removed all other sales and started from Oct 2000 to get an accurate forecast.

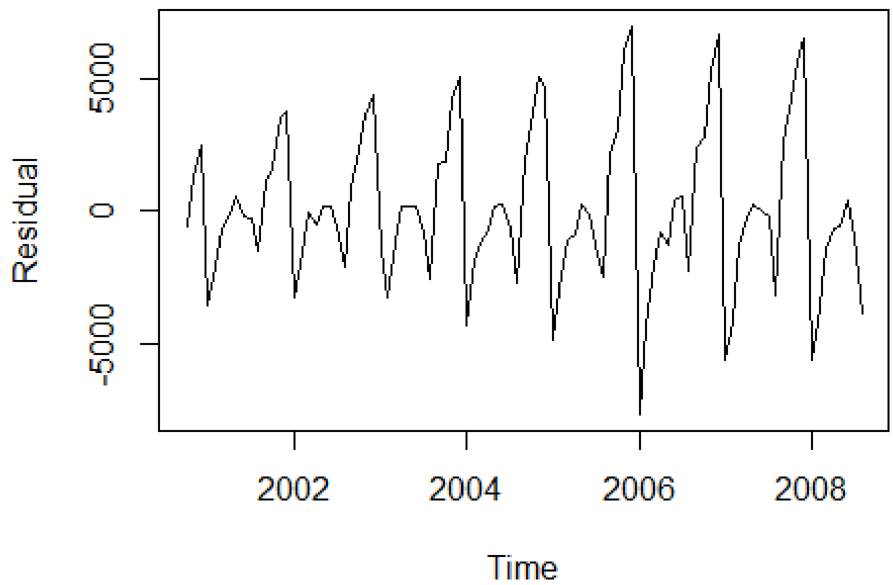
Step 2: Building Model

```
data.ts <- ts(data$Sales, start = c(2000, 10), frequency = 12, names = "sales
")
autoplot(data.ts, main = "Wine Sales", xlab = "Year", ylab = "Sales (Cases of
Wine)")
```



Simple Exponential Smoothing Method

```
ses <- ses(data.ts, alpha = 0.399, h =13)
error.ses <- data.ts - ses$fitted
rmse.ses <- round(sqrt(mean(error.ses^2)), digits = 2)
x <- scales::percent(MAPE(ses$fitted, data.ts), accuracy = 0.01)
x1 <- MeanAD(ses$fitted)
x2 <- mean(error.ses^2)
plot(error.ses, ylab = "Residual")
```



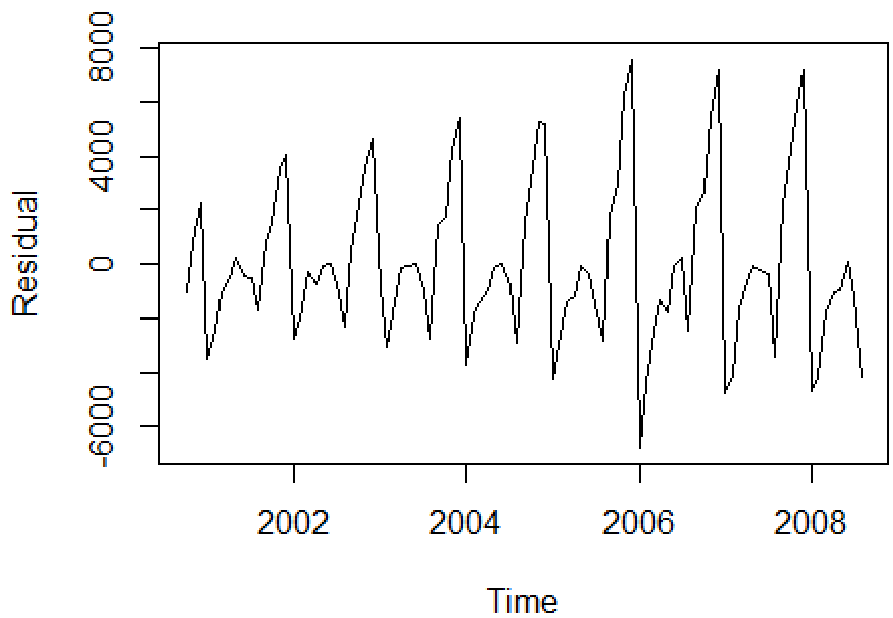

```
summary(ses)

##
## Forecast method: Simple exponential smoothing
##
## Model Information:
## Simple exponential smoothing
##
## Call:
##  ses(y = data.ts, h = 13, alpha = 0.399)
##
##   Smoothing parameters:
##     alpha = 0.399
##
##   Initial states:
##     l = 9255.0877
##
##   sigma:  2990.872
##
##      AIC     AICc      BIC
## 1955.228 1955.358 1960.336
##
## Error measures:
##                    ME     RMSE      MAE       MPE     MAPE     MASE      AC
F1
## Training set 94.95237 2959.222 2248.456 -3.132211 18.29915 1.936836 0.3112
46
```

```
##
## Forecasts:
##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Sep 2008       12854.26 9021.300 16687.21 6992.255 18716.26
## Oct 2008       12854.26 8727.458 16981.06 6542.863 19165.65
## Nov 2008       12854.26 8453.191 17255.32 6123.408 19585.11
## Dec 2008       12854.26 8195.041 17513.47 5728.602 19979.91
## Jan 2009       12854.26 7950.463 17758.05 5354.550 20353.96
## Feb 2009       12854.26 7717.516 17991.00 4998.289 20710.23
## Mar 2009       12854.26 7494.684 18213.83 4657.498 21051.02
## Apr 2009       12854.26 7280.754 18427.76 4330.320 21378.19
## May 2009       12854.26 7074.738 18633.78 4015.245 21693.27
## Jun 2009       12854.26 6875.816 18832.70 3711.021 21997.49
## Jul 2009       12854.26 6683.304 19025.21 3416.598 22291.92
## Aug 2009       12854.26 6496.618 19211.90 3131.087 22577.43
## Sep 2009       12854.26 6315.260 19393.25 2853.724 22854.79
```

Measure of Forecast Accuracy of Simple Exponential Smoothing Model AIC = RMSE = 2959.22 MAPE = 18.30% MAD = 2076.8053989 MSE = 8.756993810^{6}

Holt's Exponential Smoothing Method

```
h <- holt(data.ts, alpha= 0.314, h = 13)
error.h <- data.ts - h$fitted
rmse.h <- round(sqrt(mean(error.h^2)), digits = 2)
y <- scales::percent(MAPE(h$fitted, data.ts), accuracy = 0.01)
y1 <- MeanAD(h$fitted)
y2 <- mean(error.h^2)
plot(error.h, ylab = "Residual")
```



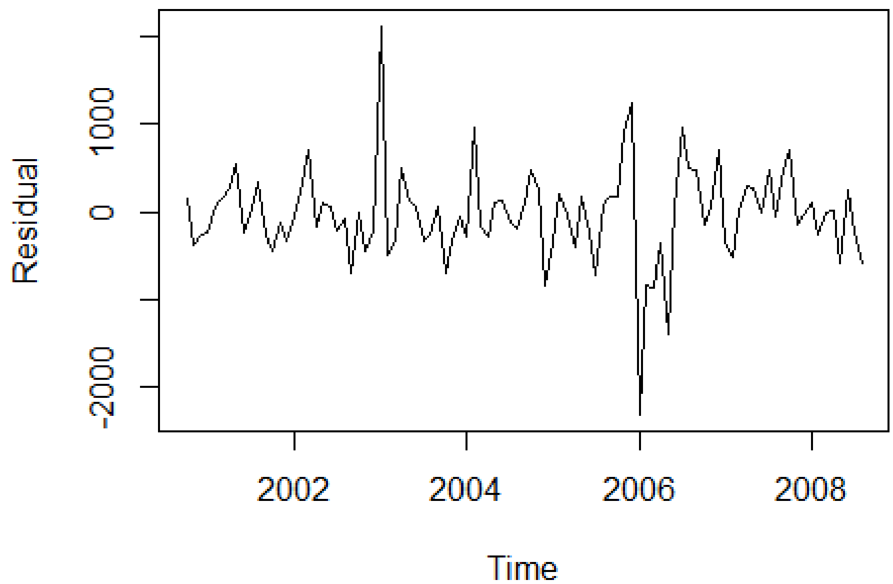

```r
summary(h)

##
## Forecast method: Holt's method
##
## Model Information:
## Holt's method
##
## Call:
##  holt(y = data.ts, h = 13, alpha = 0.314)
##
##   Smoothing parameters:
##     alpha = 0.314
##     beta  = 1e-04
##
##   Initial states:
##     l = 9661.3201
##     b = 43.732
##
##   sigma:  3025.828
##
##      AIC     AICc      BIC
## 1959.370 1959.815 1969.586
##
## Error measures:
##                      ME      RMSE       MAE        MPE       MAPE       MASE
ACF1
```

```
## Training set -14.55967 2961.441 2265.711 -4.330499 18.44019 1.951699 0.351
4548
##
## Forecasts:
##          Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Sep 2008       13431.14 9553.387 17308.90 7500.627 19361.65
## Oct 2008       13474.73 9410.192 17539.28 7258.553 19690.92
## Nov 2008       13518.33 9275.100 17761.56 7028.871 20007.79
## Dec 2008       13561.92 9147.128 17976.72 6810.077 20313.77
## Jan 2009       13605.52 9025.475 18185.56 6600.948 20610.08
## Feb 2009       13649.11 8909.480 18388.74 6400.472 20897.75
## Mar 2009       13692.70 8798.590 18586.82 6207.803 21177.60
## Apr 2009       13736.30 8692.336 18780.26 6022.224 21450.37
## May 2009       13779.89 8590.315 18969.47 5843.119 21716.66
## Jun 2009       13823.48 8492.181 19154.79 5669.960 21977.01
## Jul 2009       13867.08 8397.632 19336.52 5502.282 22231.87
## Aug 2009       13910.67 8306.403 19514.94 5339.682 22481.66
## Sep 2009       13954.26 8218.259 19690.27 5181.801 22726.73
```

Measure of Forecast Accuracy of Holt's Exponential Smoothing Model AIC = RMSE = 2961.44 MAPE = 18.44% MAD = 1978.0793419 MSE = 8.770133510^{6}

Holt Winter Exponential Smoothing Method

```
hw <- ets(data.ts, alpha = 0.282, beta = 0.001, gamma = 0.001)
sales.hw <- forecast(hw, h=13)
error.hw <- data.ts - sales.hw$fitted
rmse.hw <- round(sqrt(mean(error.hw^2)), digits = 2)
z <- scales::percent(MAPE(sales.hw$fitted, data.ts), accuracy = 0.01)
z1 <- MeanAD(sales.hw$fitted)
z2 <- mean(error.hw^2)
plot(error.hw, ylab = "Residual")
```




```
summary(hw)

## ETS(M,A,M)
##
## Call:
##  ets(y = data.ts, alpha = 0.282, beta = 0.001, gamma = 0.001)
##
##   Smoothing parameters:
##     alpha = 0.282
##     beta  = 0.001
##     gamma = 0.001
##
##   Initial states:
##     l = 7721.7073
##     b = 96.2569
##     s = 0.9661 0.699 0.8881 0.9421 0.9403 0.9217
##            0.914 0.8576 0.9003 1.5372 1.3416 1.0921
##
##   sigma:  0.0515
##
##      AIC     AICc      BIC
## 1656.712 1661.962 1692.467
##
## Training set error measures:
##                      ME      RMSE       MAE       MPE      MAPE       MASE      A
CF1
```

```
## Training set -36.04218 534.7648 365.9314 -0.49156 3.193968 0.3152158 0.065
367
```

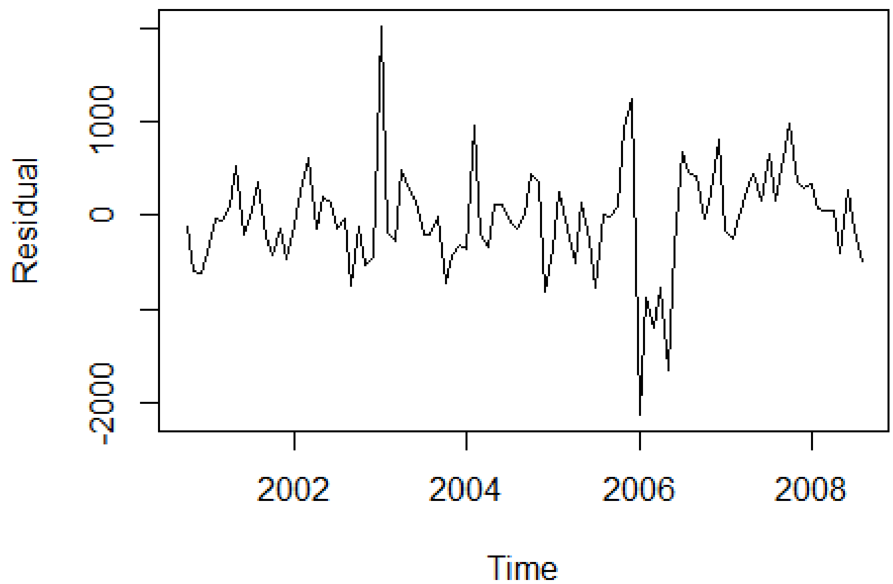
```
sales.hw$mean
```

```
##           Jan      Feb      Mar      Apr      May      Jun      Jul      A
ug
## 2008
## 2009 14499.73 13891.57 14889.62 15100.57 15491.37 15608.82 14795.42 11709.
48
##           Sep      Oct      Nov      Dec
## 2008 15203.73 17288.10 21360.18 24616.60
## 2009 16273.87
```

Measure of Forecast Accuracy of Holt Winter Exponential Smoothing Model AIC = 1656.7124343 RMSE = 534.76 MAPE = 3.19% MAD = 2521.5527541 MSE = 2.859733910^{5}

Building model with optimized parameter with ets

```
ets <- ets(data.ts)
sales.ets <- forecast(ets, h=13)
error.ets <- data.ts - sales.ets$fitted
rmse.ets <- round(sqrt(mean(error.ets^2)), digits = 2)
w <- scales::percent(MAPE(sales.ets$fitted, data.ts), accuracy = 0.01)
w1 <- MeanAD(sales.ets$fitted)
w2 <- mean(error.ets^2)
plot(error.ets, ylab = "Residual")
```




```
ets

## ETS(M,A,M)
##
## Call:
##  ets(y = data.ts)
##
##   Smoothing parameters:
##     alpha = 0.1437
##     beta  = 0.0046
##     gamma = 1e-04
##
##   Initial states:
##     l = 7964.6064
##     b = 99.257
##     s = 0.97 0.6953 0.886 0.942 0.9371 0.9278
##            0.9192 0.8484 0.8998 1.5437 1.3381 1.0925
##
##   sigma:  0.0523
##
##      AIC     AICc      BIC
## 1665.967 1673.915 1709.383
```

Measure of Forecast Accuracy of Optimized Exponential Smoothing Model AIC = 1665.9668102 RMSE = 558.4 MAPE = 3.39% MAD = 2508.0024806 MSE = 3.118094810^{5}

```
#Data Frame of Chosen Model
hw.dataframe <- data.frame(sales.hw$mean)
view(hw.dataframe)
sum(hw.dataframe[2:13, ])

## [1] 195525.3

#Question 6 (240000 cases - forecast cases)*price per case ($100)
sum(hw.dataframe[2:13, ])

## [1] 195525.3

juice.sell <- 240000 - sum(hw.dataframe[2:13, ])
juice.sell

## [1] 44474.68

#Economic Impact ($100) per case.
juice.sell*100

## [1] 4447468
```

#THE END