# Capstone project Sales prediction

Shivani Gupta

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## > Setting working directory

```
path<-"D:/data science/Capstone Project"
setwd(path)
```

## Reading the data file

```
Sales_data<-read.csv("sales_case_study.csv", header=T)
head(Sales_data, 10)
```

```
##          SKU ISO_Week Sales Season
## 1  ProductA  2018-01     0 WINTER
## 2  ProductA  2018-02     0 WINTER
## 3  ProductA  2018-03     0 WINTER
## 4  ProductA  2018-04  6988 WINTER
## 5  ProductA  2018-04  6988 WINTER
## 6  ProductA  2018-05  6743 WINTER
## 7  ProductA  2018-06  4112 WINTER
## 8  ProductA  2018-07  5732 WINTER
## 9  ProductA  2018-08    NA WINTER
## 10 ProductA  2018-09  5559 SPRING
```

#Subsetting the dataframe into 3 SKUs

```
ProductA<-subset(Sales_data, SKU=="ProductA")
ProductB<-subset(Sales_data, SKU=="ProductB")
ProductC<-subset(Sales_data, SKU=="ProductC")
```

**EDA**

## Cleaning the Data set

*Initial zero removal* There are some SKU's for which initial week's sales values are 0. It means sales started only after that period. Those weeks needs to be removed before fitting the data into the model.

*considering Initial weeks to be till 5th week We remove zero sales upto 5th week for all SKUs if any.*

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

filter(ProductA, Sales=="0")

##        SKU ISO_Week Sales Season
## 1 ProductA  2018-01     0 WINTER
## 2 ProductA  2018-02     0 WINTER
## 3 ProductA  2018-03     0 WINTER

ProductA<-ProductA[-c(1,2,3),]

filter(ProductB, Sales=="0")

##         SKU ISO_Week Sales Season
## 1  ProductB  2018-04     0 WINTER
## 2  ProductB  2018-13     0 SPRING
## 3  ProductB  2018-14     0 SPRING
## 4  ProductB  2018-15     0 SPRING
## 5  ProductB  2018-16     0 SPRING
## 6  ProductB  2018-17     0 SPRING
## 7  ProductB  2018-18     0 SPRING
## 8  ProductB  2018-19     0 SPRING
## 9  ProductB  2018-27     0 SUMMER
## 10 ProductB  2018-28     0 SUMMER
## 11 ProductB  2018-30     0 SUMMER
## 12 ProductB  2018-31     0 SUMMER
## 13 ProductB  2018-32     0 SUMMER
## 14 ProductB  2018-40     0 AUTUMN
## 15 ProductB  2018-41     0 AUTUMN
## 16 ProductB  2018-43     0 AUTUMN
## 17 ProductB  2018-44     0 AUTUMN
## 18 ProductB  2018-45     0 AUTUMN

# No initial zeros in Product B as NA values will be replaced by average on
later step

filter(ProductC, Sales=="0")

## [1] SKU      ISO_Week Sales    Season
## <0 rows> (or 0-length row.names)

# There are no initial zeros in Product C
```

*Duplicate Value Treatment* Removing duplicate rows

```
duplicated(ProductA)
```

```
##  [1] FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [13] FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [25] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [37] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [49] FALSE FALSE FALSE
```

```
ProductA[duplicated(ProductA),]
```

```
##         SKU ISO_Week Sales Season
## 5  ProductA  2018-04  6988 WINTER
## 17 ProductA  2018-15 10012 SPRING
```

```
ProductA<-distinct(ProductA)
```

```
duplicated(ProductB)
```

```
##  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE
FALSE
## [13] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [25] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [37] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [49] FALSE FALSE FALSE FALSE FALSE
```

```
ProductB[duplicated(ProductB),]
```

```
##         SKU ISO_Week Sales Season
## 63 ProductB  2018-08   219 WINTER
```

```
ProductB<-distinct(ProductB)
```

```
duplicated(ProductC)
```

```
##  [1] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [13] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [25] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
FALSE
## [37] FALSE FALSE FALSE FALSE FALSE FALSE FALSE
```

```
ProductC[duplicated(ProductC),]
```

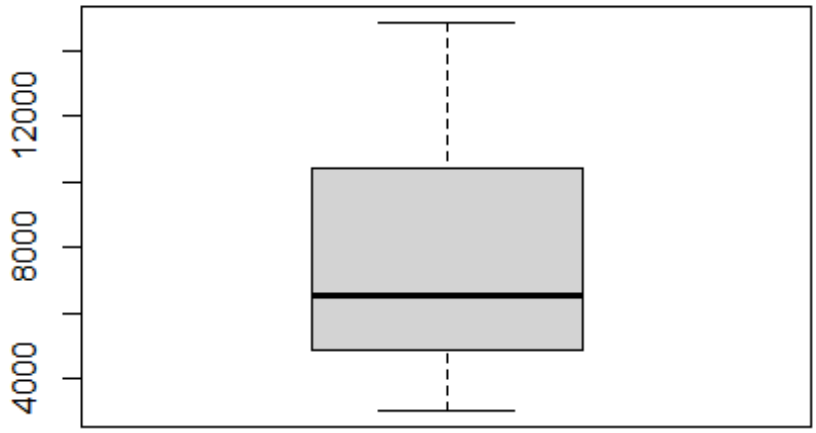
```
##          SKU ISO_Week Sales Season
## 113 ProductC  2018-15  5533 SPRING

ProductC<-distinct(ProductC)
```

*Missing Value Treatment*

```
sum(is.na(ProductA))

## [1] 4

Averages<-ProductA %>% group_by(Season) %>% summarise(average = mean(Sales,
na.rm=TRUE))
ProductA[5,3]<-9600.125
ProductA[15,3]<-9027.154
ProductA[26,3]<-5942.091
ProductA[27,3]<-5942.091

sum(is.na(ProductB))

## [1] 3

AveragesB<-ProductB %>% group_by(Season) %>% summarise(average = mean(Sales,
na.rm=TRUE))
ProductB[1,3]<-397.8750
ProductB[2,3]<-397.8750
ProductB[3,3]<-397.8750

sum(is.na(ProductC))

## [1] 0

# No NA values present in Product C
```

*Outlier treatment* Product A

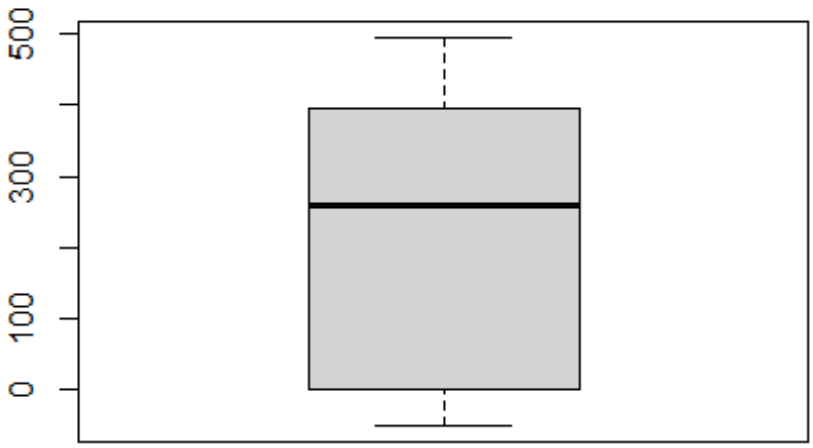
```
boxplot(ProductA$Sales)
```




```
# No outlier in Product A
```

Product B

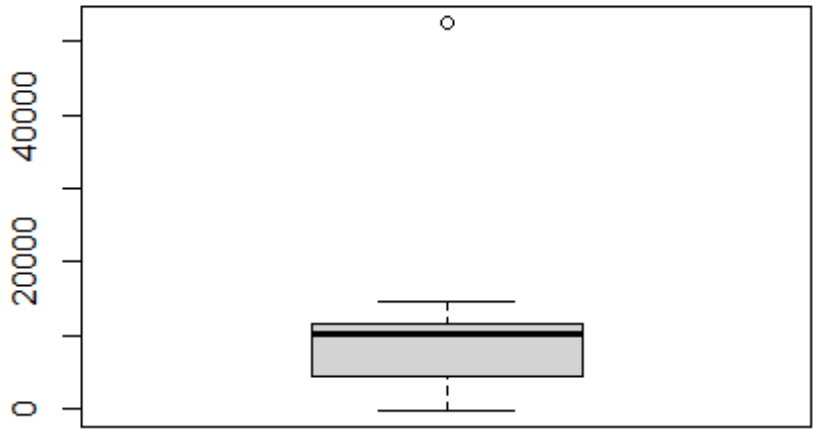
```
boxplot(ProductB$Sales)
```




```
# No outlier in Product B
```

## Replacing outlier with mean in Product C

```
boxplot(ProductC$Sales)
```




```
AveragesC<-ProductC %>% group_by(Season) %>% summarise(average = mean(Sales,
na.rm=TRUE))
outliers <- boxplot(ProductC$Sales, plot=FALSE)$out
ProductC$Sales<-replace(ProductC$Sales, ProductC$Sales==52524,14072.385)
```

*Replacing negative values with zero*

```
ProductA[ProductA$Sales<0,]

## [1] SKU      ISO_Week Sales    Season
## <0 rows> (or 0-length row.names)

ProductB[ProductB$Sales<0,]

##         SKU ISO_Week Sales Season
## 12 ProductB  2018-12   -50 SPRING
## 29 ProductB  2018-29   -45 SUMMER
## 42 ProductB  2018-42   -23 AUTUMN

ProductB$Sales<-replace(ProductB$Sales, ProductB$Sales<0, 0)

ProductC[ProductC$Sales<0,]

##         SKU ISO_Week Sales Season
## 7  ProductC  2018-17  -111 SPRING
## 8  ProductC  2018-18  -149 SPRING
## 9  ProductC  2018-19  -163 SPRING
## 10 ProductC  2018-20  -119 SPRING
```

```
ProductC$Sales<-replace(ProductC$Sales, ProductC$Sales<0, 0)
```

#Checking summary and structure

```
summary(ProductA)
```

```
##      SKU              ISO_Week            Sales          Season
##  Length:49          Length:49          Min.   : 3036   Length:49
##  Class :character   Class :character   1st Qu.: 4874   Class :character
##  Mode  :character   Mode  :character   Median : 6568   Mode  :character
##                                        Mean   : 7519
##                                        3rd Qu.:10410
##                                        Max.   :14853
```

```
str(ProductA)
```

```
## 'data.frame':    49 obs. of  4 variables:
##  $ SKU     : chr  "ProductA" "ProductA" "ProductA" "ProductA" ...
##  $ ISO_Week: chr  "2018-04" "2018-05" "2018-06" "2018-07" ...
##  $ Sales   : num  6988 6743 4112 5732 9600 ...
##  $ Season  : chr  "WINTER" "WINTER" "WINTER" "WINTER" ...
```

```
summary(ProductB)
```

```
##      SKU              ISO_Week            Sales          Season
##  Length:52          Length:52          Min.   :  0.0   Length:52
##  Class :character   Class :character   1st Qu.:  0.0   Class :character
##  Mode  :character   Mode  :character   Median :259.5   Mode  :character
##                                        Mean   :221.1
##                                        3rd Qu.:393.5
##                                        Max.   :495.0
```

```
str(ProductB)
```

```
## 'data.frame':    52 obs. of  4 variables:
##  $ SKU     : chr  "ProductB" "ProductB" "ProductB" "ProductB" ...
##  $ ISO_Week: chr  "2018-01" "2018-02" "2018-03" "2018-04" ...
##  $ Sales   : num  398 398 398 0 446 ...
##  $ Season  : chr  "WINTER" "WINTER" "WINTER" "WINTER" ...
```

```
summary(ProductC)
```

```
##      SKU              ISO_Week            Sales          Season
##  Length:42          Length:42          Min.   :    0   Length:42
##  Class :character   Class :character   1st Qu.: 4415   Class :character
##  Mode  :character   Mode  :character   Median :10192   Mode  :character
##                                        Mean   : 8244
##                                        3rd Qu.:11592
##                                        Max.   :14521
```

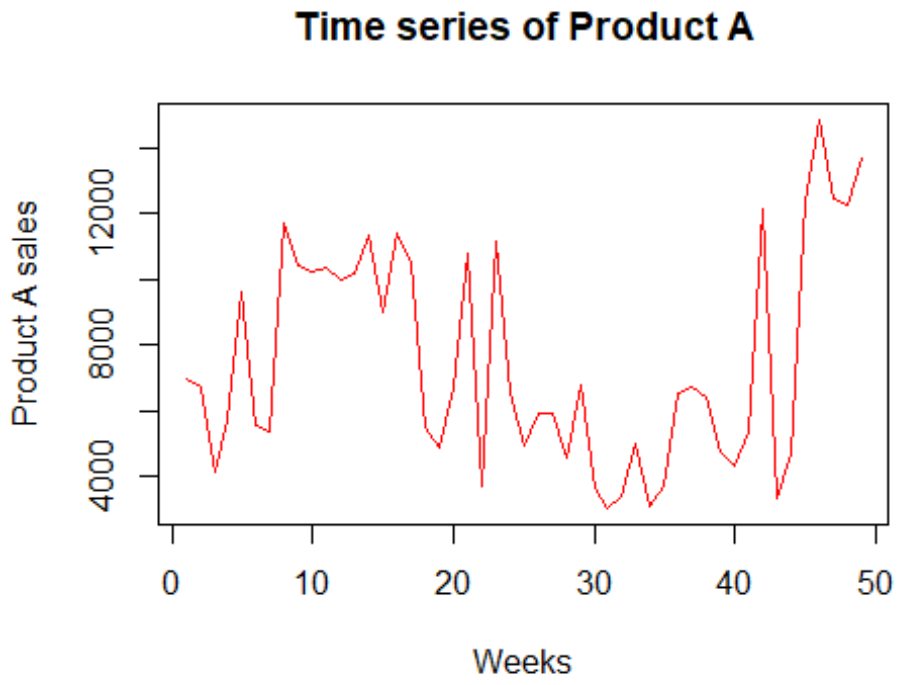
```
str(ProductC)
```

```
## 'data.frame':    42 obs. of  4 variables:
##  $ SKU     : chr  "ProductC" "ProductC" "ProductC" "ProductC" ...
##  $ ISO_Week: chr  "2018-11" "2018-12" "2018-13" "2018-14" ...
##  $ Sales   : num  5495 6330 6144 6383 5533 ...
##  $ Season  : chr  "SPRING" "SPRING" "SPRING" "SPRING" ...
```

## Visualising Data

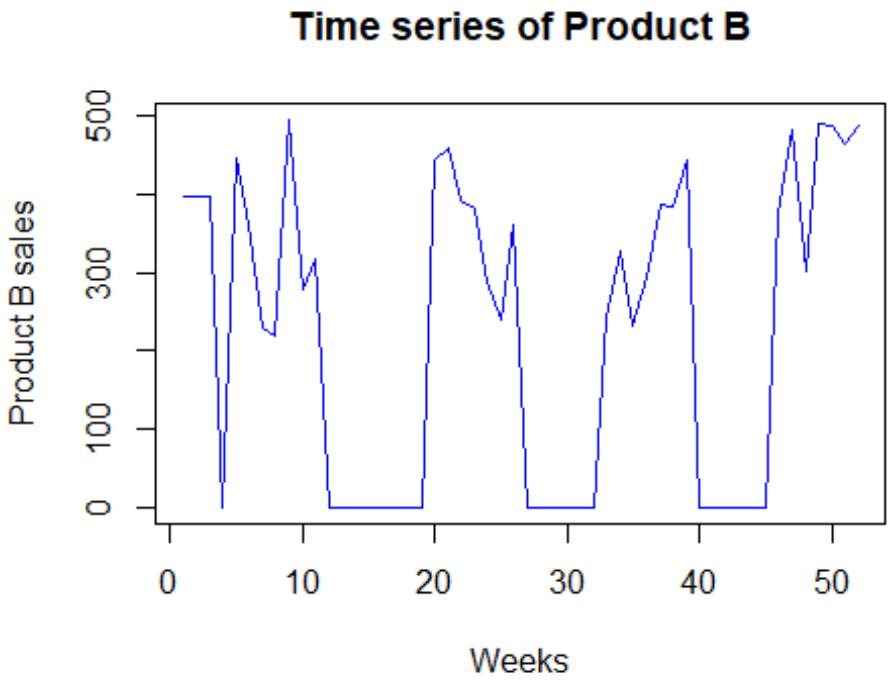
*Product A*

```
plot.ts(ProductA$Sales, col="Red", main="Time series of Product A",
ylab="Product A sales", xlab="Weeks")
```



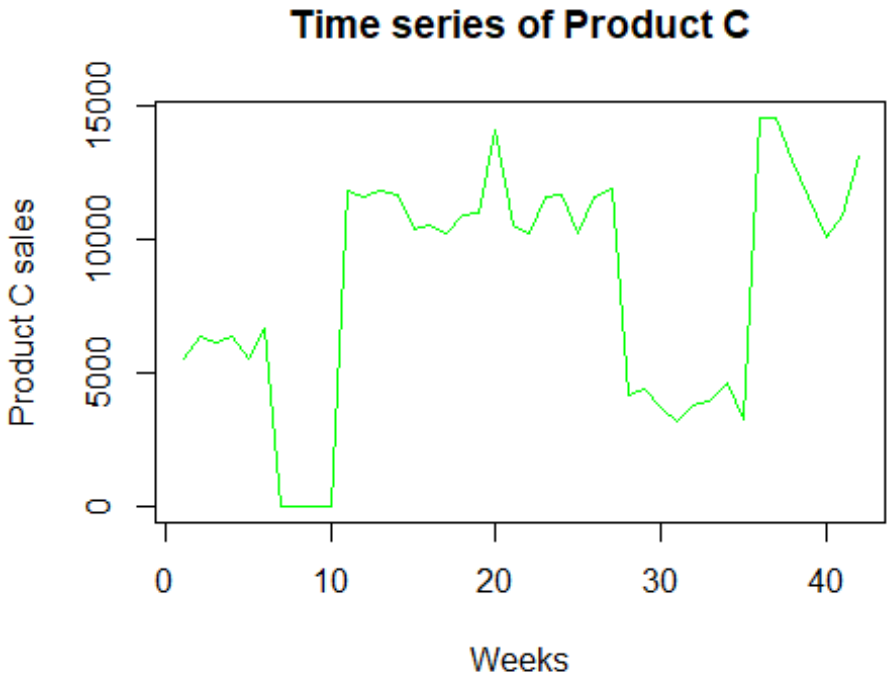

*Product B*

```
plot.ts(ProductB$Sales, col="Blue", main="Time series of Product B",
ylab="Product B sales", xlab="Weeks")
```




*Product C*

```
plot.ts(ProductC$Sales, col="Green", main="Time series of Product C",
ylab="Product C sales", xlab="Weeks")
```



#Dividing into Training And Testing Dataset

```
trainA<-ProductA[1:38,]
TestA<-ProductA[39:49,]

trainB<-ProductB[1:41,]
TestB<-ProductB[42:52,]

trainC<-ProductC[1:31,]
TestC<-ProductC[32:42,]
```

## Fitting into model ARIMA

```
#install.packages("forecast")
library(forecast)

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

fitA<-auto.arima(as.ts(trainA$Sales), stepwise=FALSE, approximation=FALSE)
fitB<-auto.arima(as.ts(trainB$Sales), stepwise=FALSE, approximation=FALSE)
fitC<-auto.arima(as.ts(trainC$Sales), stepwise=FALSE, approximation=FALSE)


ForecastA <-forecast(fitA,h=11)
ForecastB <-forecast(fitB,h=11)
ForecastC <-forecast(fitC,h=11)


accuracy(ForecastA,TestA$Sales)

##                      ME     RMSE      MAE       MPE     MAPE      MASE
## Training set  -63.58775 2330.254 1795.271 -11.30124 29.95325 0.8735753
## Test set     3252.24100 5394.183 4494.402  14.37814 45.15375 2.1869671
##                   ACF1
## Training set -0.051369
## Test set            NA

accuracy(ForecastB, TestB$Sales)

##                      ME     RMSE      MAE  MPE MAPE     MASE        ACF1
## Training set -3.254217 155.0201 125.0011 -Inf  Inf 1.203127 -0.0190718
## Test set     97.384994 218.9796 206.9214 -Inf  Inf 1.991604          NA

accuracy(ForecastC, TestC$Sales)

##                      ME     RMSE      MAE      MPE     MAPE     MASE
ACF1
## Training set   61.94718 2814.795 1852.785     -Inf      Inf 1.222697
0.04304937
```

```
## Test set     3073.56723 4818.061 4087.098 13.81509 41.97441 2.697175
NA
```

## Forecasted data using ARIMA

```
Fr_salesA<-data.frame(ForecastA)
Fr_salesB<-data.frame(ForecastB)
Fr_salesC<-data.frame(ForecastC)

output_table<-read.csv("output.csv")
Fr_salesA[,1]
```

```
##  [1] 5852.577 5852.577 5852.577 5852.577 5852.577 5852.577 5852.577
5852.577
##  [9] 5852.577 5852.577 5852.577
```

```
SKU<-output_table$SKU
ISO_week<-output_table$ISO_Week
Pred_Arima<-
c(Fr_salesA$Point.Forecast,Fr_salesB$Point.Forecast,Fr_salesC$Point.Forecast)
output<-data.frame(cbind(SKU,ISO_week,Pred_Arima))
print(output)
```

```
##         SKU ISO_week       Pred_Arima
## 1  ProductA  2018-42 5852.57717848706
## 2  ProductA  2018-43 5852.57717848706
## 3  ProductA  2018-44 5852.57717848706
## 4  ProductA  2018-45 5852.57717848706
## 5  ProductA  2018-46 5852.57717848706
## 6  ProductA  2018-47 5852.57717848706
## 7  ProductA  2018-48 5852.57717848706
## 8  ProductA  2018-49 5852.57717848706
## 9  ProductA  2018-50 5852.57717848706
## 10 ProductA  2018-51 5852.57717848706
## 11 ProductA  2018-52 5852.57717848706
## 12 ProductB  2018-42 95.1183691737332
## 13 ProductB  2018-43 146.055997014545
## 14 ProductB  2018-44 173.334029140075
## 15 ProductB  2018-45 187.941914669547
## 16 ProductB  2018-46 195.764704768927
## 17 ProductB  2018-47 199.953952063855
## 18 ProductB  2018-48 202.197370674748
## 19 ProductB  2018-49 203.398762406813
## 20 ProductB  2018-50 204.042129670892
## 21 ProductB  2018-51 204.386664617688
## 22 ProductB  2018-52 204.571169388433
## 23 ProductC  2018-42 4255.91404243336
## 24 ProductC  2018-43 5063.49963112302
## 25 ProductC  2018-44  5657.5301816511
## 26 ProductC  2018-45 6094.47742278904
```

```
## 27 ProductC  2018-46 6415.87990178331
## 28 ProductC  2018-47 6652.29186134767
## 29 ProductC  2018-48 6826.18788977892
## 30 ProductC  2018-49 6954.09947580817
## 31 ProductC  2018-50 7048.18658054609
## 32 ProductC  2018-51 7117.39362857644
## 33 ProductC  2018-52 7168.29981290867
```

## Fitting data into Model ETS

```
modelA<-ets(trainA$Sales)
modelB<-ets(trainB$Sales)
modelC<-ets(trainC$Sales)

PredictA<-predict(modelA, h=11)
PredictB<-predict(modelB, h=11)
PredictC<-predict(modelC, h=11)

accuracy(PredictA,TestA$Sales)
```

```
##                       ME     RMSE      MAE       MPE     MAPE      MASE
## Training set  -61.32686 2329.721 1813.403 -11.41182 30.29308 0.8823982
## Test set     3295.52809 5420.392 4498.337  15.01142 44.88702 2.1888820
##                      ACF1
## Training set -0.03874678
## Test set              NA
```

```
accuracy(PredictB, TestB$Sales)
```

```
##                      ME     RMSE      MAE  MPE MAPE     MASE        ACF1
## Training set -12.38388 167.1241 108.0049 -Inf  Inf 1.039539 0.007062978
## Test set     239.10879 324.3193 269.3768 -Inf  Inf 2.592732          NA
```

```
accuracy(PredictC, TestC$Sales)
```

```
##                       ME     RMSE      MAE      MPE     MAPE     MASE
## Training set  -84.18031 2970.083 1521.921     -Inf      Inf 1.004352
## Test set     6148.70032 7536.322 6150.275 52.61385 52.66289 4.058715
##                      ACF1
## Training set 0.0001862073
## Test set               NA
```

#Forecasted data using ets

```
Pr_salesA<-data.frame(PredictA)
Pr_salesB<-data.frame(PredictB)
Pr_salesC<-data.frame(PredictC)



SKU<-output_table$SKU
```

```
ISO_week<-output_table$ISO_Week
Pred_Arima<-
c(Fr_salesA$Point.Forecast,Fr_salesB$Point.Forecast,Fr_salesC$Point.Forecast)
output<-data.frame(cbind(SKU,ISO_week,Pred_Arima))
output$Pred_ets<-
c(Pr_salesA$Point.Forecast,Pr_salesB$Point.Forecast,Pr_salesC$Point.Forecast)
print(output)
```

```
##         SKU ISO_week       Pred_Arima   Pred_ets
## 1  ProductA  2018-42 5852.57717848706 5809.29009
## 2  ProductA  2018-43 5852.57717848706 5809.29009
## 3  ProductA  2018-44 5852.57717848706 5809.29009
## 4  ProductA  2018-45 5852.57717848706 5809.29009
## 5  ProductA  2018-46 5852.57717848706 5809.29009
## 6  ProductA  2018-47 5852.57717848706 5809.29009
## 7  ProductA  2018-48 5852.57717848706 5809.29009
## 8  ProductA  2018-49 5852.57717848706 5809.29009
## 9  ProductA  2018-50 5852.57717848706 5809.29009
## 10 ProductA  2018-51 5852.57717848706 5809.29009
## 11 ProductA  2018-52 5852.57717848706 5809.29009
## 12 ProductB  2018-42 95.1183691737332   41.61848
## 13 ProductB  2018-43 146.055997014545   41.61848
## 14 ProductB  2018-44 173.334029140075   41.61848
## 15 ProductB  2018-45 187.941914669547   41.61848
## 16 ProductB  2018-46 195.764704768927   41.61848
## 17 ProductB  2018-47 199.953952063855   41.61848
## 18 ProductB  2018-48 202.197370674748   41.61848
## 19 ProductB  2018-49 203.398762406813   41.61848
## 20 ProductB  2018-50 204.042129670892   41.61848
## 21 ProductB  2018-51 204.386664617688   41.61848
## 22 ProductB  2018-52 204.571169388433   41.61848
## 23 ProductC  2018-42 4255.91404243336 3220.66332
## 24 ProductC  2018-43 5063.49963112302 3220.66332
## 25 ProductC  2018-44  5657.5301816511 3220.66332
## 26 ProductC  2018-45 6094.47742278904 3220.66332
## 27 ProductC  2018-46 6415.87990178331 3220.66332
## 28 ProductC  2018-47 6652.29186134767 3220.66332
## 29 ProductC  2018-48 6826.18788977892 3220.66332
## 30 ProductC  2018-49 6954.09947580817 3220.66332
## 31 ProductC  2018-50 7048.18658054609 3220.66332
## 32 ProductC  2018-51 7117.39362857644 3220.66332
## 33 ProductC  2018-52 7168.29981290867 3220.66332
```