Final Demand Forecast

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# Load and clean data

The file loaded is the telecommunication companies´s subscribers by ten years, for each service provided by this companies. The service offering are: Internet residential and business, Video on demand and VoIP.

library(caret)

## Loading required package: lattice

## Loading required package: ggplot2

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 7.1

library(growthmodels)  
  
subs<-read.csv("C:/Users/NataliaA/Documents/DataR/Subscribers\_CV.csv",header=TRUE,  
 sep=";",na.strings="NA",dec=",")  
  
years<-na.exclude(subs[1])  
oper1<-na.exclude(subs[1:5]) #Subs operador 1  
oper2<-data.frame(years,na.exclude(subs[6:9])) #Subs operador 2  
oper3<-data.frame(years,na.exclude(subs[10:13])) #Subs operador 3

# Data Preparation

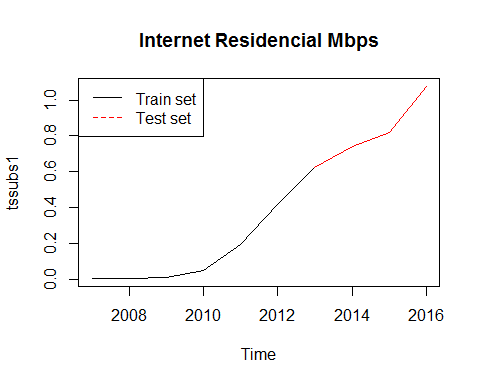
year<-years$Year  
start<-year[1]  
hi<-dim(years)[1]  
end<-year[hi]  
year1<-year[round(hi\*0.70)]  
  
seth<-8 ##Set predictions quantity  
f1<-end+1 #Q forecast  
f2<-end+5 #Q forecast  
  
time<-1:hi

# Demand Models for Internet Residential Subscribers

## 1.1 Predicting with Growth curves InRes

Simple random sampling of time series is probably not the best way to resample times series data. Hyndman and Athanasopoulos (2013)) discuss rolling forecasting origin techniques that move the training and test sets in time.

#Operator1  
tssubs1<-ts(oper1$Internet\_Res1,start=start,end=end) #Time serie  
tsset1<-tssubs1  
tstrain1<-window(tsset1,start=start,end=year1) #Training and Testing data  
tstest1<-window(tsset1,start=year1,end=end)   
  
#Operator2  
tssubs2<-ts(oper2$Internet\_Res2,start=start,end=end) #Time serie  
tsset2<-tssubs2/1  
tstrain2<-window(tsset2,start=start,end=year1) #Training and Testing data  
tstest2<-window(tsset2,start=year1,end=end)   
  
#Operator3  
tssubs3<-ts(oper3$Internet\_Res3,start=start,end=end) #Time serie  
tsset3<-tssubs3/1  
tstrain3<-window(tsset3,start=start,end=year1) #Training and Testing data  
tstest3<-window(tsset3,start=year1,end=end)  
  
plot(tssubs1,main="Internet Residencial Mbps")  
lines(tstest1,col="red")  
legend("topleft",legend = c("Train set","Test set"), col=c("black","red"), lty = 1:2)



### Linear Model

#Operator 1  
fitlm1<-tslm(tstrain1~trend) #Model  
predlm1<-forecast(fitlm1, h=seth) #Prediction  
#Operator 2  
fitlm2<-tslm(tstrain2~trend) #Model  
predlm2<-forecast(fitlm2, h=seth) #Prediction  
#Operator 3  
fitlm3<-tslm(tstrain3~trend) #Model  
predlm3<-forecast(fitlm3, h=seth) #Prediction

### Parabolic Model

#Operator 1  
fitpar1=lm(tsset1 ~ time + I(time^2)) #Model  
predpar1<-predict(fitpar1) #Prediction  
forepar1<-forecast(predpar1,h=seth-3) #Forecast  
#Operator 2  
fitpar2=lm(tsset2 ~ time + I(time^2)) #Model  
predpar2<-predict(fitpar2) #Prediction  
forepar2<-forecast(predpar2,h=seth-3) #Forecast  
#Operator 3  
fitpar3=lm(tsset3 ~ time + I(time^2)) #Model   
predpar3<-predict(fitpar3) #Prediction  
forepar3<-forecast(predpar3,h=seth-3) #Forecast

### Exponential Model

#Operator 1  
Yexp1=lm(log(tsset1) ~ time) #Transform  
parmexp1<-as.list(Yexp1$coeff)  
betae1<- exp(parmexp1$"(Intercept)") #growth range (a)  
ke1<- parmexp1$time #growth rate (b)  
fitexp1<-betae1\*exp(ke1\*time) #Model  
predexp1<-forecast(fitexp1,h=seth-3)  
  
#Operator 2  
Yexp2=lm(log(tsset2) ~ time) #Transform  
parmexp2<-as.list(Yexp2$coeff)  
betae2<- exp(parmexp2$"(Intercept)") #growth range (a)  
ke2<- parmexp2$time #growth rate (b)  
fitexp2<-betae2\*exp(ke2\*time) #Model  
predexp2<-forecast(fitexp2,h=seth-3)  
  
#Operator 3  
Yexp3=lm(log(tsset3) ~ time) #Transform  
parmexp3<-as.list(Yexp3$coeff)  
betae3<- exp(parmexp3$"(Intercept)") #growth range (a)  
ke3<- parmexp3$time #growth rate (b)  
fitexp3<-betae3\*exp(ke3\*time) #Model  
predexp3<-forecast(fitexp3,h=seth-3)

### The predictions with growth curves are:

#Operator 1  
set1a<-data.frame(predlm1) #Linear predictions  
lma<-data.frame(Fore\_Lin1=set1a$Point.Forecast[4:8])  
data\_predlm1<-data.frame(Lin1=c(fitlm1$fitted.values,set1a$Point.Forecast[1:3]))  
#Operator 2  
set1b<-data.frame(predlm2) #Linear predictions  
lmb<-data.frame(Fore\_Lin2=set1b$Point.Forecast[4:8])  
data\_predlm2<-data.frame(Lin2=c(fitlm2$fitted.values,set1b$Point.Forecast[1:3]))  
#Operator 3  
set1c<-data.frame(predlm3) #Linear predictions  
lmc<-data.frame(Fore\_Lin3=set1c$Point.Forecast[4:8])  
data\_predlm3<-data.frame(Lin3=c(fitlm3$fitted.values,set1c$Point.Forecast[1:3]))  
  
  
#Operator 1  
data\_predpar1<-data.frame(Par1=predpar1) #Parabolic predictions  
set2a<-data.frame(forepar1)  
para<-data.frame(Fore\_Par1=set2a$Point.Forecast)  
#Operator 2  
data\_predpar2<-data.frame(Par2=predpar2) #Parabolic predictions  
set2b<-data.frame(forepar2)  
parb<-data.frame(Fore\_Par2=set2b$Point.Forecast)  
#Operator 3  
data\_predpar3<-data.frame(Par3=predpar3) #Parabolic predictions  
set2c<-data.frame(forepar3)  
parc<-data.frame(Fore\_Par3=set2c$Point.Forecast)  
  
  
#Operator 1  
set3a<-data.frame(predexp1) #Exponential predictions  
expa<-data.frame(Fore\_Exp1=set3a$Point.Forecast)  
data\_predexp1<-data.frame(Exp1=fitexp1)  
#Operator 2  
set3b<-data.frame(predexp2) #Exponential predictions  
expb<-data.frame(Fore\_Exp2=set3b$Point.Forecast)  
data\_predexp2<-data.frame(Exp2=fitexp2)  
#Operator 1  
set3c<-data.frame(predexp3) #Exponential predictions  
expc<-data.frame(Fore\_Exp3=set3c$Point.Forecast)  
data\_predexp3<-data.frame(Exp3=fitexp3)  
  
  
##Sets of predictions  
data\_pred1a<-data.frame(data\_predlm1,data\_predpar1,data\_predexp1) #Operator 1  
data\_pred2a<-data.frame(data\_predlm2,data\_predpar2,data\_predexp2) #Operator 2  
data\_pred3a<-data.frame(data\_predlm3,data\_predpar3,data\_predexp3) #Operator 3

### Forecasting for 5 Years are:

fore1a<-data.frame(Year=f1:f2,lma,para,expa) #Operator 1  
fore1b<-data.frame(lmb,parb,expb) #Operator 2  
fore1c<-data.frame(lmc,parc,expc) #Operator 3

## 1.2 Predicting with Logistic and Gompertz Model InRes

### Logistic Model

Using the **growthmodels** package, with the *logistic* function to get the logistic curve **Usage** logistic(t, alpha, beta, k) **Arguments** t time,x size, alpha upper asymptote, beta growth range, k growth rate

#Operator 1  
alpha1<-tssubs1[hi] +0.5 #upper asymptote (M)  
Y1<-log(alpha1/tssubs1-1) #Transform  
Reglm1<-tslm(Y1~trend) #Lineal Regression  
parmlm1<-as.list(Reglm1$coeff)  
  
beta1<- exp(parmlm1$"(Intercept)") #growth range (a)  
k1<- -parmlm1$trend #growth rate (b)  
fitlog1 <- logistic(1:10, alpha1, beta1, k1)  
predlog1<-forecast(fitlog1,h=seth)  
  
#Operator 2  
alpha2<-tssubs2[hi] +0.5 #upper asymptote (M)  
Y2<-log(alpha2/tssubs2-1) #Transform  
Reglm2<-tslm(Y2~trend) #Lineal Regression  
parmlm2<-as.list(Reglm2$coeff)  
  
beta2<- exp(parmlm2$"(Intercept)") #growth range (a)  
k2<- -parmlm2$trend #growth rate (b)  
fitlog2 <- logistic(1:10, alpha2, beta2, k2)  
predlog2<-forecast(fitlog2,h=seth)  
  
#Operator 3  
alpha3<-tssubs3[hi] +0.5 #upper asymptote (M)  
Y3<-log(alpha3/tssubs3-1) #Transform  
Reglm3<-tslm(Y3~trend) #Lineal Regression  
parmlm3<-as.list(Reglm3$coeff)  
  
beta3<- exp(parmlm3$"(Intercept)") #growth range (a)  
k3<- -parmlm3$trend #growth rate (b)  
fitlog3 <- logistic(1:10, alpha3, beta3, k3)  
predlog3<-forecast(fitlog3,h=seth)

The predictions using logistic model are:

set4a<-data.frame(predlog1)  
alog<-set4a$Point.Forecast #Operator 1 predictions  
set4b<-data.frame(predlog2)  
blog<-set4b$Point.Forecast #Operator 2 predictions  
set4c<-data.frame(predlog3)  
clog<-set4c$Point.Forecast #Operator 3 predictions  
  
data\_predlog1<-data.frame(Log1=fitlog1)  
data\_predlog2<-data.frame(Log2=fitlog2)  
data\_predlog3<-data.frame(Log3=fitlog3)

### Gompertz Model

Using the **growthmodels** package, Computes the Gompertz growth model **Usage** gompertz(t, alpha, beta, k) **Arguments** t time x size alpha upper asymptote beta growth displacement k growth rate

#Operator 1  
alphag1<-tssubs1[hi] +5 #upper asymptote (M)  
Y1g<-log(log(alphag1/tssubs1)) #Transform  
Reglmg1<-tslm(Y1g~trend) #Lineal Regression  
parmglm1<-as.list(Reglmg1$coeff)  
  
betag1<- exp(parmglm1$"(Intercept)") #growth range (a)  
kg1<- -parmglm1$trend #growth rate (b)  
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)  
predgom1<-forecast(fitgom1,h=seth)  
  
#Operator 2  
alphag2<-tssubs2[hi] +5 #upper asymptote (M)  
Y2g<-log(log(alphag2/tssubs2)) #Transform  
Reglmg2<-tslm(Y2g~trend) #Lineal Regression  
parmglm2<-as.list(Reglmg2$coeff)  
  
betag2<- exp(parmglm2$"(Intercept)") #growth range (a)  
kg2<- -parmglm2$trend #growth rate (b)  
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)  
predgom2<-forecast(fitgom2,h=seth)  
  
#Operator 3  
alphag3<-tssubs3[hi] +5 #upper asymptote (M)  
Y3g<-log(log(alphag3/tssubs3)) #Transform  
Reglmg3<-tslm(Y3g~trend) #Lineal Regression  
parmglm3<-as.list(Reglmg3$coeff)  
  
betag3<- exp(parmglm3$"(Intercept)") #growth range (a)  
kg3<- -parmglm3$trend #growth rate (b)  
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)  
predgom3<-forecast(fitgom3,h=seth)

The predictions using gompertz model are:

set5a<-data.frame(predgom1)  
agom<-set5a$Point.Forecast #Operator 1 predictions  
set5b<-data.frame(predgom2)  
bgom<-set5b$Point.Forecast #Operator 2 predictions  
set5c<-data.frame(predgom3)  
cgom<-set5c$Point.Forecast #Operator 3 predictions  
  
data\_predgom1<-data.frame(Gom1=fitgom1)  
data\_predgom2<-data.frame(Gom2=fitgom2)  
data\_predgom3<-data.frame(Gom3=fitgom3)

### Forecasting for 5 years

fore2a<-data.frame(Fore\_Log1=alog[1:5],Fore\_Gom1=agom[1:5])  
fore2b<-data.frame(Fore\_Log2=blog[1:5],Fore\_Gom1=bgom[1:5])  
fore2c<-data.frame(Fore\_Log3=clog[1:5],Fore\_Gom1=cgom[1:5])

## 1.3 Performance Models for Internet Residential

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error #**(MAE)**: Mean Absolute Error **(MPE)**: Mean Porcentual Error **(MAPE)**: Mean Absolute Porcentual Error

#Modelo Lineal  
acc\_d1<-accuracy(predlm1) #Operator 1  
acc\_d2<-accuracy(predlm2) #Operator 2  
acc\_d3<-accuracy(predlm3) #Operator 3  
  
#Modelo Parabólico  
acc\_e1<-accuracy(predpar1,tsset1) #Operator 1  
acc\_e2<-accuracy(predpar2,tsset2) #Operator 2  
acc\_e3<-accuracy(predpar3,tsset3) #Operator 3  
  
#Modelo Exponencial  
acc\_f1<-accuracy(predexp1) #Operator 1   
acc\_f2<-accuracy(predexp2) #Operator 2   
acc\_f3<-accuracy(predexp3) #Operator 3   
  
#Modelo Logístico  
acc\_g1<-accuracy(predlog1) #Operator 1   
acc\_g2<-accuracy(predlog2) #Operator 2   
acc\_g3<-accuracy(predlog3) #Operator 3   
  
#Modelo Gompertz  
acc\_h1<-accuracy(predgom1) #Operator 1   
acc\_h2<-accuracy(predgom2) #Operator 2   
acc\_h3<-accuracy(predgom3) #Operator 3

The performance sets are:

Models<-c("Linear","Parabolic","Exponential","Logistic","Gompertz")  
  
#Opereator 1   
accd1<-acc\_d1[1,1:5] #Linear  
acce1<-acc\_e1[1,1:5] #Parabolic  
accf1<-acc\_f1[1,1:5] #Exponential  
accg1<-acc\_g1[1,1:5] #Logistic  
acch1<-acc\_h1[1,1:5] #Gompertz  
acc\_all1b<-round(rbind(accd1,acce1,accf1,accg1,acch1),2)  
performIRes1<-data.frame(Models,acc\_all1b)  
  
#Operator 2  
accd2<-acc\_d2[1,1:5]  
acce2<-acc\_e2[1,1:5]  
accf2<-acc\_f2[1,1:5]  
accg2<-acc\_g2[1,1:5]  
acch2<-acc\_h2[1,1:5]  
acc\_all2b<-round(rbind(accd2,acce1,accf1,accg1,acch1),2)  
performIRes2<-data.frame(Models,acc\_all2b)  
  
#Operator 3  
accd3<-acc\_d3[1,1:5]  
acce3<-acc\_e3[1,1:5]  
accf3<-acc\_f3[1,1:5]  
accg3<-acc\_g3[1,1:5]  
acch3<-acc\_h3[1,1:5]  
acc\_all3b<-round(rbind(accd3,acce1,accf1,accg1,acch1),2)  
performIRes3<-data.frame(Models,acc\_all3b)

## Predictions Reports

### Internet Residential Predictions by service provider

predIRes1<-data.frame(data\_pred1a,data\_predlog1,data\_predgom1) #Operator 1   
predIRes2<-data.frame(data\_pred2a,data\_predlog2,data\_predgom2) #Operator 2   
predIRes3<-data.frame(data\_pred3a,data\_predlog3,data\_predgom3) #Operator 3

### Forecast Reports

Forecasting for 5 Years Internet Residential

foreIRes1<-data.frame(fore1a,fore2a) #Operator 1  
foreIRes2<-data.frame(fore1b,fore2b) #Operator 2  
foreIRes3<-data.frame(fore1c,fore2c) #Operator 3

# Demand Models for Internet Bussines Subscribers

## Preparation Data

#Operator1  
tssubs1<-ts(oper1$Internet\_Bus1,start=start,end=end) #Time serie  
tsset1<-tssubs1  
tstrain1<-window(tsset1,start=start,end=year1) #Training and Testing data  
tstest1<-window(tsset1,start=year1,end=end)   
  
#Operator2  
tssubs2<-ts(oper2$Internet\_Bus2,start=start,end=end) #Time serie  
tsset2<-tssubs2/1  
tstrain2<-window(tsset2,start=start,end=year1) #Training and Testing data  
tstest2<-window(tsset2,start=year1,end=end)   
  
#Operator3  
tssubs3<-ts(oper3$Internet\_Bus3,start=start,end=end) #Time serie  
tsset3<-tssubs3/1  
tstrain3<-window(tsset3,start=start,end=year1) #Training and Testing data  
tstest3<-window(tsset3,start=year1,end=end)

## 2.1 Predicting with Growth curves InBus

### Linear Model

#Operator 1  
fitlm1<-tslm(tstrain1~trend) #Model  
predlm1<-forecast(fitlm1, h=seth) #Prediction  
#Operator 2  
fitlm2<-tslm(tstrain2~trend) #Model  
predlm2<-forecast(fitlm2, h=seth) #Prediction  
#Operator 3  
fitlm3<-tslm(tstrain3~trend) #Model  
predlm3<-forecast(fitlm3, h=seth) #Prediction

### Parabolic Model

#Operator 1  
fitpar1=lm(tsset1 ~ time + I(time^2)) #Model  
predpar1<-predict(fitpar1) #Prediction  
forepar1<-forecast(predpar1,h=seth-3) #Forecast  
#Operator 2  
fitpar2=lm(tsset2 ~ time + I(time^2)) #Model  
predpar2<-predict(fitpar2) #Prediction  
forepar2<-forecast(predpar2,h=seth-3) #Forecast  
#Operator 3  
fitpar3=lm(tsset3 ~ time + I(time^2)) #Model   
predpar3<-predict(fitpar3) #Prediction  
forepar3<-forecast(predpar3,h=seth-3) #Forecast

### Exponential Model

#Operator 1  
Yexp1=lm(log(tsset1) ~ time,na.action=) #Transform  
parmexp1<-as.list(Yexp1$coeff)  
betae1<- exp(parmexp1$"(Intercept)") #growth range (a)  
ke1<- parmexp1$time #growth rate (b)  
fitexp1<-betae1\*exp(ke1\*time) #Model  
predexp1<-forecast(fitexp1,h=seth-3)  
  
#Operator 2  
Yexp2=lm(log(tsset2) ~ time) #Transform  
parmexp2<-as.list(Yexp2$coeff)  
betae2<- exp(parmexp2$"(Intercept)") #growth range (a)  
ke2<- parmexp2$time #growth rate (b)  
fitexp2<-betae2\*exp(ke2\*time) #Model  
predexp2<-forecast(fitexp2,h=seth-3)  
  
#Operator 3  
Yexp3=lm(log(tsset3) ~ time) #Transform  
parmexp3<-as.list(Yexp3$coeff)  
betae3<- exp(parmexp3$"(Intercept)") #growth range (a)  
ke3<- parmexp3$time #growth rate (b)  
fitexp3<-betae3\*exp(ke3\*time) #Model  
predexp3<-forecast(fitexp3,h=seth-3)

The predictions with growth curves are:

#Operator 1  
set1a<-data.frame(predlm1) #Linear predictions  
lma<-data.frame(Fore\_Lin1=set1a$Point.Forecast[4:8])  
data\_predlm1<-data.frame(Lin1=c(fitlm1$fitted.values,set1a$Point.Forecast[1:3]))  
#Operator 2  
set1b<-data.frame(predlm2) #Linear predictions  
lmb<-data.frame(Fore\_Lin2=set1b$Point.Forecast[4:8])  
data\_predlm2<-data.frame(Lin2=c(fitlm2$fitted.values,set1b$Point.Forecast[1:3]))  
#Operator 3  
set1c<-data.frame(predlm3) #Linear predictions  
lmc<-data.frame(Fore\_Lin3=set1c$Point.Forecast[4:8])  
data\_predlm3<-data.frame(Lin3=c(fitlm3$fitted.values,set1c$Point.Forecast[1:3]))  
  
  
#Operator 1  
data\_predpar1<-data.frame(Par1=predpar1) #Parabolic predictions  
set2a<-data.frame(forepar1)  
para<-data.frame(Fore\_Par1=set2a$Point.Forecast)  
#Operator 2  
data\_predpar2<-data.frame(Par2=predpar2) #Parabolic predictions  
set2b<-data.frame(forepar2)  
parb<-data.frame(Fore\_Par2=set2b$Point.Forecast)  
#Operator 3  
data\_predpar3<-data.frame(Par3=predpar3) #Parabolic predictions  
set2c<-data.frame(forepar3)  
parc<-data.frame(Fore\_Par3=set2c$Point.Forecast)  
  
  
#Operator 1  
set3a<-data.frame(predexp1) #Exponential predictions  
expa<-data.frame(Fore\_Exp1=set3a$Point.Forecast)  
data\_predexp1<-data.frame(Exp1=fitexp1)  
#Operator 2  
set3b<-data.frame(predexp2) #Exponential predictions  
expb<-data.frame(Fore\_Exp2=set3b$Point.Forecast)  
data\_predexp2<-data.frame(Exp2=fitexp2)  
#Operator 1  
set3c<-data.frame(predexp3) #Exponential predictions  
expc<-data.frame(Fore\_Exp3=set3c$Point.Forecast)  
data\_predexp3<-data.frame(Exp3=fitexp3)  
  
  
##Sets of predictions  
data\_pred1b<-data.frame(data\_predlm1,data\_predpar1,data\_predexp1) #Operator 1  
data\_pred2b<-data.frame(data\_predlm2,data\_predpar2,data\_predexp2) #Operator 2  
data\_pred3b<-data.frame(data\_predlm3,data\_predpar3,data\_predexp3) #Operator 3  
  
##Forecasting for 5 Years  
fore3a<-data.frame(Year=f1:f2,lma,para,expa) #Operator 1  
fore3b<-data.frame(lmb,parb,expb) #Operator 2  
fore3c<-data.frame(lmc,parc,expc) #Operator 3

## 2.2.Predicting with Logistic and Gompertz Model InBus

### Logistic Model

#Operator 1  
alpha1<-tssubs1[hi] +0.5 #upper asymptote (M)  
Y1<-log(alpha1/tssubs1-1) #Transform  
Reglm1<-tslm(Y1~trend) #Lineal Regression  
parmlm1<-as.list(Reglm1$coeff)  
  
beta1<- exp(parmlm1$"(Intercept)") #growth range (a)  
k1<- -parmlm1$trend #growth rate (b)  
fitlog1 <- logistic(1:10, alpha1, beta1, k1)  
predlog1<-forecast(fitlog1,h=seth)  
  
#Operator 2  
alpha2<-tssubs2[hi] +0.5 #upper asymptote (M)  
Y2<-log(alpha2/tssubs2-1) #Transform  
Reglm2<-tslm(Y2~trend) #Lineal Regression  
parmlm2<-as.list(Reglm2$coeff)  
  
beta2<- exp(parmlm2$"(Intercept)") #growth range (a)  
k2<- -parmlm2$trend #growth rate (b)  
fitlog2 <- logistic(1:10, alpha2, beta2, k2)  
predlog2<-forecast(fitlog2,h=seth)  
  
#Operator 3  
alpha3<-tssubs3[hi] +0.5 #upper asymptote (M)  
Y3<-log(alpha3/tssubs3-1) #Transform  
Reglm3<-tslm(Y3~trend) #Lineal Regression  
parmlm3<-as.list(Reglm3$coeff)  
  
beta3<- exp(parmlm3$"(Intercept)") #growth range (a)  
k3<- -parmlm3$trend #growth rate (b)  
fitlog3 <- logistic(1:10, alpha3, beta3, k3)  
predlog3<-forecast(fitlog3,h=seth)

The predictions using logistic model are:

set4a<-data.frame(predlog1)  
alog<-set4a$Point.Forecast #Operator 1 predictions  
set4b<-data.frame(predlog2)  
blog<-set4b$Point.Forecast #Operator 2 predictions  
set4c<-data.frame(predlog3)  
clog<-set4c$Point.Forecast #Operator 3 predictions  
  
data\_predlog1<-data.frame(Log1=fitlog1)  
data\_predlog2<-data.frame(Log2=fitlog2)  
data\_predlog3<-data.frame(Log3=fitlog3)

### Gompertz Model

#Operator 1  
alphag1<-tssubs1[hi] +5 #upper asymptote (M)  
Y1g<-log(log(alphag1/tssubs1)) #Transform  
Reglmg1<-tslm(Y1g~trend) #Lineal Regression  
parmglm1<-as.list(Reglmg1$coeff)  
  
betag1<- exp(parmglm1$"(Intercept)") #growth range (a)  
kg1<- -parmglm1$trend #growth rate (b)  
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)  
predgom1<-forecast(fitgom1,h=seth)  
  
#Operator 2  
alphag2<-tssubs2[hi] +5 #upper asymptote (M)  
Y2g<-log(log(alphag2/tssubs2)) #Transform  
Reglmg2<-tslm(Y2g~trend) #Lineal Regression  
parmglm2<-as.list(Reglmg2$coeff)  
  
betag2<- exp(parmglm2$"(Intercept)") #growth range (a)  
kg2<- -parmglm2$trend #growth rate (b)  
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)  
predgom2<-forecast(fitgom2,h=seth)  
  
#Operator 3  
alphag3<-tssubs3[hi] +5 #upper asymptote (M)  
Y3g<-log(log(alphag3/tssubs3)) #Transform  
Reglmg3<-tslm(Y3g~trend) #Lineal Regression  
parmglm3<-as.list(Reglmg3$coeff)  
  
betag3<- exp(parmglm3$"(Intercept)") #growth range (a)  
kg3<- -parmglm3$trend #growth rate (b)  
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)  
predgom3<-forecast(fitgom3,h=seth)

The predictions using gompertz model are:

set5a<-data.frame(predgom1)  
agom<-set5a$Point.Forecast #Operator 1 predictions  
set5b<-data.frame(predgom2)  
bgom<-set5b$Point.Forecast #Operator 2 predictions  
set5c<-data.frame(predgom3)  
cgom<-set5c$Point.Forecast #Operator 3 predictions  
  
data\_predgom1<-data.frame(Gom1=fitgom1)  
data\_predgom2<-data.frame(Gom2=fitgom2)  
data\_predgom3<-data.frame(Gom3=fitgom3)

### Forecasting for 5 years

fore4a<-data.frame(Fore\_Log1=alog[1:5],Fore\_Gom1=agom[1:5])  
fore4b<-data.frame(Fore\_Log2=blog[1:5],Fore\_Gom1=bgom[1:5])  
fore4c<-data.frame(Fore\_Log3=clog[1:5],Fore\_Gom1=cgom[1:5])

## 2.3.Performance Models for Internet Bussines

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error **(MAE)**: Mean Absolute Error **(MPE)**: Mean Porcentual Error **(MAPE)**: Mean Absolute Porcentual Error

#Modelo Lineal  
acc\_d1<-accuracy(predlm1) #Operator 1  
acc\_d2<-accuracy(predlm2) #Operator 2  
acc\_d3<-accuracy(predlm3) #Operator 3  
  
#Modelo Parabólico  
acc\_e1<-accuracy(predpar1,tsset1) #Operator 1  
acc\_e2<-accuracy(predpar2,tsset2) #Operator 2  
acc\_e3<-accuracy(predpar3,tsset3) #Operator 3  
  
#Modelo Exponencial  
acc\_f1<-accuracy(predexp1) #Operator 1   
acc\_f2<-accuracy(predexp2) #Operator 2   
acc\_f3<-accuracy(predexp3) #Operator 3   
  
#Modelo Logístico  
acc\_g1<-accuracy(predlog1) #Operator 1   
acc\_g2<-accuracy(predlog2) #Operator 2   
acc\_g3<-accuracy(predlog3) #Operator 3   
  
#Modelo Gompertz  
acc\_h1<-accuracy(predgom1) #Operator 1   
acc\_h2<-accuracy(predgom2) #Operator 2   
acc\_h3<-accuracy(predgom3) #Operator 3   
  
#The performance sets are:  
Models<-c("Linear","Parabolic","Exponential","Logistic","Gompertz")  
  
#Opereator 1   
accd1<-acc\_d1[1,1:5] #Linear  
acce1<-acc\_e1[1,1:5] #Parabolic  
accf1<-acc\_f1[1,1:5] #Exponential  
accg1<-acc\_g1[1,1:5] #Logistic  
acch1<-acc\_h1[1,1:5] #Gompertz  
acc\_all1b<-round(rbind(accd1,acce1,accf1,accg1,acch1),2)  
performIBus1<-data.frame(Models,acc\_all1b)  
  
#Operator 2  
accd2<-acc\_d2[1,1:5]  
acce2<-acc\_e2[1,1:5]  
accf2<-acc\_f2[1,1:5]  
accg2<-acc\_g2[1,1:5]  
acch2<-acc\_h2[1,1:5]  
acc\_all2b<-round(rbind(accd2,acce2,accf2,accg2,acch2),2)  
performIBus2<-data.frame(Models,acc\_all2b)  
  
#Operator 3  
accd3<-acc\_d3[1,1:5]  
acce3<-acc\_e3[1,1:5]  
accf3<-acc\_f3[1,1:5]  
accg3<-acc\_g3[1,1:5]  
acch3<-acc\_h3[1,1:5]  
acc\_all3b<-round(rbind(accd3,acce3,accf3,accg3,acch3),2)  
performIBus3<-data.frame(Models,acc\_all3b)

## Predictions Report

Internet Bussines Predictions by service provider

predIBus1<-data.frame(data\_pred1b,data\_predlog1,data\_predgom1) #Operator 1   
predIBus2<-data.frame(data\_pred2b,data\_predlog2,data\_predgom2) #Operator 2   
predIBus3<-data.frame(data\_pred3b,data\_predlog3,data\_predgom3) #Operator 3

## Forecast Reports

Forecasting for 5 Years Internet Residential

foreIBus1<-data.frame(fore3a,fore4a) #Operator 1  
foreIBus2<-data.frame(fore3b,fore4b) #Operator 2  
foreIBus3<-data.frame(fore3c,fore4c) #Operator 3

# 3.Demand Models for VoD Subscribers

## Subset data

dataVoD1<-data.frame(Year=year,Subs=oper1$VoD1) #Operator 1  
tssubs1<-ts(oper1$VoD1,start=start,end=end) #Time serie  
dataVoD2<-data.frame(Year=year,Subs=oper2$VoD2) #Operator 2  
tssubs2<-ts(oper2$VoD2,start=start,end=end) #Time serie  
dataVoD3<-data.frame(Year=year,Subs=oper3$VoD3) #Operator 3  
tssubs3<-ts(oper3$VoD3,start=start,end=end) #Time serie

## 3.1.Predicting with Logistic and Gompertz Model VoD

## Logistic Model

#Operator 1  
alpha1<-tssubs1[hi] +0.5 #upper asymptote (M)  
Y1<-log(alpha1/tssubs1-1)\*1 #Transform  
Reglm1<-tslm(Y1~trend) #Lineal Regression #ERROR  
parmlm1<-as.list(Reglm1$coeff)  
  
beta1<- exp(parmlm1$"(Intercept)") #growth range (a)  
k1<- -parmlm1$trend #growth rate (b)  
fitlog1 <- logistic(1:10, alpha1, beta1, k1)  
predlog1<-forecast(fitlog1,h=seth)  
  
#Operator 2  
alpha2<-tssubs2[hi] +0.5 #upper asymptote (M)  
Y2<-log(alpha2/tssubs2-1) #Transform  
Reglm2<-tslm(Y2~trend) #Lineal Regression  
parmlm2<-as.list(Reglm2$coeff)  
  
beta2<- exp(parmlm2$"(Intercept)") #growth range (a)  
k2<- -parmlm2$trend #growth rate (b)  
fitlog2 <- logistic(1:10, alpha2, beta2, k2)  
predlog2<-forecast(fitlog2,h=seth)  
  
#Operator 3  
alpha3<-tssubs3[hi] +0.5 #upper asymptote (M)  
Y3<-log(alpha3/tssubs3-1) #Transform  
Reglm3<-tslm(Y3~trend) #Lineal Regression  
parmlm3<-as.list(Reglm3$coeff)  
  
beta3<- exp(parmlm3$"(Intercept)") #growth range (a)  
k3<- -parmlm3$trend #growth rate (b)  
fitlog3 <- logistic(1:10, alpha3, beta3, k3)  
predlog3<-forecast(fitlog3,h=seth)

## The predictions using logistic model are:

set4a<-data.frame(predlog1)  
alog<-set4a$Point.Forecast #Operator 1 predictions  
set4b<-data.frame(predlog2)  
blog<-set4b$Point.Forecast #Operator 2 predictions  
set4c<-data.frame(predlog3)  
clog<-set4c$Point.Forecast #Operator 3 predictions  
  
data\_predlog1<-data.frame(Log1=fitlog1)  
data\_predlog2<-data.frame(Log2=fitlog2)  
data\_predlog3<-data.frame(Log3=fitlog3)

### Gompertz Model

Using the **growthmodels** package, Computes the Gompertz growth model **Usage** gompertz(t, alpha, beta, k) **Arguments** t time x size alpha upper asymptote beta growth displacement k growth rate

#Operator 1  
alphag1<-tssubs1[hi] +5 #upper asymptote (M)  
Y1g<-log(log(alphag1/tssubs1)) #Transform  
Reglmg1<-tslm(Y1g~trend) #Lineal Regression  
parmglm1<-as.list(Reglmg1$coeff)  
  
betag1<- exp(parmglm1$"(Intercept)") #growth range (a)  
kg1<- -parmglm1$trend #growth rate (b)  
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)  
predgom1<-forecast(fitgom1,h=seth)  
  
#Operator 2  
alphag2<-tssubs2[hi] +5 #upper asymptote (M)  
Y2g<-log(log(alphag2/tssubs2)) #Transform  
Reglmg2<-tslm(Y2g~trend) #Lineal Regression  
parmglm2<-as.list(Reglmg2$coeff)  
  
betag2<- exp(parmglm2$"(Intercept)") #growth range (a)  
kg2<- -parmglm2$trend #growth rate (b)  
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)  
predgom2<-forecast(fitgom2,h=seth)  
  
#Operator 3  
alphag3<-tssubs3[hi] +5 #upper asymptote (M)  
Y3g<-log(log(alphag3/tssubs3)) #Transform  
Reglmg3<-tslm(Y3g~trend) #Lineal Regression  
parmglm3<-as.list(Reglmg3$coeff)  
  
betag3<- exp(parmglm3$"(Intercept)") #growth range (a)  
kg3<- -parmglm3$trend #growth rate (b)  
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)  
predgom3<-forecast(fitgom3,h=seth)

## The predictions using gompertz model are:

set5a<-data.frame(predgom1)  
agom<-set5a$Point.Forecast #Operator 1 predictions  
set5b<-data.frame(predgom2)  
bgom<-set5b$Point.Forecast #Operator 2 predictions  
set5c<-data.frame(predgom3)  
cgom<-set5c$Point.Forecast #Operator 3 predictions  
  
data\_predgom1<-data.frame(Gom1=fitgom1)  
data\_predgom2<-data.frame(Gom2=fitgom2)  
data\_predgom3<-data.frame(Gom3=fitgom3)

### Parabolic Model----------------------REV

#Operator 1  
fitpar1=lm(tssubs1 ~ time + I(time^2)) #Model  
predpar1<-predict(fitpar1) #Prediction  
forepar1<-forecast(predpar1,h=seth-3) #Forecast  
#Operator 2  
fitpar2=lm(tssubs2 ~ time + I(time^2)) #Model  
predpar2<-predict(fitpar2) #Prediction  
forepar2<-forecast(predpar2,h=seth-3) #Forecast  
#Operator 3  
fitpar3=lm(tssubs3 ~ time + I(time^2)) #Model   
predpar3<-predict(fitpar3) #Prediction  
forepar3<-forecast(predpar3,h=seth-3) #Forecast

## Forecasting for 5 years

fore5a<-data.frame(Fore\_Log1=alog[1:5],Fore\_Gom1=agom[1:5],Fore\_Par1=forepar1)  
fore5b<-data.frame(Fore\_Log2=blog[1:5],Fore\_Gom2=bgom[1:5],Fore\_Par2=forepar2)  
fore5c<-data.frame(Fore\_Log3=clog[1:5],Fore\_Gom3=cgom[1:5],Fore\_Par3=forepar3)

## 3.2.Predicting with Fisher Pry

Model applied When substitution is driven by superior technology. The new product or service presents some technological advantage over the old one.

#Operator 1  
L1<-tssubs1[hi]+5 #upper asymptote (L)  
transf1<-log((L1-tssubs1)/tssubs1) #transform  
  
fitpry1<-tslm(transf1~trend) #model  
set5a<-fitpry1$fitted.values  
predpry1<-L1/(1+exp(set5a)) #Prediction  
forepry1<-forecast(predpry1,h=seth) #Forecast  
  
#Operator 2  
L2<-tssubs2[hi]+5 #upper asymptote (L)  
transf2<-log((L2-tssubs2)/tssubs2) #transform  
  
fitpry2<-tslm(transf2~trend) #model  
set5b<-fitpry2$fitted.values  
predpry2<-L2/(1+exp(set5b)) #Prediction  
forepry2<-forecast(predpry2,h=seth) #Forecast  
  
#Operator 3  
L3<-tssubs3[hi]+5 #upper asymptote (L)  
transf3<-log((L3-tssubs3)/tssubs3) #transform  
  
fitpry3<-tslm(transf3~trend) #model  
set5c<-fitpry3$fitted.values  
predpry3<-L3/(1+exp(set5c)) #Prediction  
forepry3<-forecast(predpry3,h=seth) #Forecast

## 3.3. Bass Model

**m** Total number of potential buyers of the new product **p** The coefficient of innovation **q** The coefficient of imitation

#Operator1  
setbas1<-subset(dataVoD1,Subs>=0.101)  
setbas2<-subset(dataVoD1,Subs<0.101)  
demand1<-tssubs1#[(tssubs1)>=0.101]  
   
time<-1:length(demand1)  
Tdelt <- time #Accuracy, size predictions  
  
Bass.nls <- nls(demand1 ~ M \* (((P + Q)^2/P) \* exp(-(P + Q) \* time))/(1 + (Q/P)   
 \*exp(-(P + Q) \* time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))  
  
Bcoef <- coef(Bass.nls) # get coefficient operator 1  
m <- Bcoef[1]  
p <- Bcoef[2]  
q <- Bcoef[3]  
ngete <- exp(-(p + q) \* Tdelt) #Setting the starting values for M to the Subs  
  
fitbas1 <- m \* ((p + q)^2/p) \* ngete/(1 + (q/p) \* ngete)^2 #Model  
  
setbas3<-data.frame(Year=dataVoD1$Year,Subs=fitbas1) #Prediction  
x<-nrow(setbas2)  
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x\*0))  
predbas1<-rbind(setbas3)  
forebas1<-forecast(predbas1$Subs,h=seth) #Forecast  
  
#Operator2  
setbas1<-subset(dataVoD2,Subs>=0.101)  
setbas2<-subset(dataVoD2,Subs<0.101)  
demand2<-tssubs2[(tssubs2)>=0.101]  
time<-1:length(demand2)  
Tdelt <- time #Accuracy, size predictions  
  
Bass.nls <- nls(demand2 ~ M \* (((P + Q)^2/P)\*exp(-(P + Q) \* time))/  
 (1 + (Q/P)\*exp(-(P + Q) \* time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))  
Bcoef <- coef(Bass.nls) # get coefficient operator 1  
m <- Bcoef[1]  
p <- Bcoef[2]  
q <- Bcoef[3]  
ngete <- exp(-(p + q) \* Tdelt) #Setting the starting values for M to the Subs  
  
fitbas2 <- m \* ((p + q)^2/p) \* ngete/(1 + (q/p) \* ngete)^2 #Model  
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas2) #Prediction  
x<-nrow(setbas2)  
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x\*0))  
predbas2<-rbind(cero,setbas3)  
forebas2<-forecast(predbas2$Subs,h=seth) #Forecast  
  
#Operator3  
setbas1<-subset(dataVoD3,Subs>=0.101)  
setbas2<-subset(dataVoD3,Subs<0.101)  
demand3<-tssubs3[(tssubs3)>=0.101]  
time<-1:length(demand3)  
Tdelt <- time #Accuracy, size predictions  
  
Bass.nls <- nls(demand3 ~ M \* (((P + Q)^2/P) \* exp(-(P + Q) \* time))/(1 + (Q/P)   
 \*exp(-(P + Q) \* time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))  
Bcoef <- coef(Bass.nls) # get coefficient operator 1  
m <- Bcoef[1]  
p <- Bcoef[2]  
q <- Bcoef[3]  
ngete <- exp(-(p + q) \* Tdelt) #Setting the starting values for M to the Subs  
  
fitbas3 <- m \* ((p + q)^2/p) \* ngete/(1 + (q/p) \* ngete)^2 #Model  
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas3) #Prediction  
x<-nrow(setbas2)  
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x\*0))  
predbas3<-rbind(cero,setbas3)  
forebas3<-forecast(predbas3$Subs,h=seth) #Forecast

The predictions using Bass and Fisher Pry model are:

set6a<-data.frame(forepry1)  
apry<-set6a$Point.Forecast #Operator 1 predictions  
set6b<-data.frame(forepry2)  
bpry<-set6b$Point.Forecast #Operator 2 predictions  
set6c<-data.frame(forepry3)  
cpry<-set6c$Point.Forecast #Operator 3 predictions  
  
set7a<-data.frame(forebas1)  
abas<-set7a$Point.Forecast #Operator 1 predictions  
set7b<-data.frame(forebas2)  
bbas<-set7b$Point.Forecast #Operator 2 predictions  
set7c<-data.frame(forebas3)  
cbas<-set7c$Point.Forecast #Operator 3 predictions  
  
data\_pred1c<-data.frame(Pry1=predpry1,Bass1=predbas1$Subs)  
data\_pred2c<-data.frame(Pry2=predpry2,Bass2=predbas2$Subs)  
data\_pred3c<-data.frame(Pry3=predpry3,Bass3=predbas3$Subs)

# Forecasting for 5 years

fore6a<-data.frame(Fore\_Pry1=apry[1:5],Fore\_Bas1=abas[1:5])  
fore6b<-data.frame(Fore\_Pry2=bpry[1:5],Fore\_Bas2=bbas[1:5])  
fore6c<-data.frame(Fore\_Pry3=cpry[1:5],Fore\_Bas3=cbas[1:5])

## 3.4.Performance Models for VoD

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error **(MAE)**: Mean Absolute Error \*(MPE)**: Mean Porcentual Error** (MAPE)\*\*: Mean Absolute Porcentual Error

#Modelo Parabólico  
acc\_e1<-accuracy(predpar1,tssubs1) #Operator 1  
acc\_e2<-accuracy(predpar2,tssubs2) #Operator 2  
acc\_e3<-accuracy(predpar3,tssubs3) #Operator 3  
  
#Modelo Logístico  
acc\_g1<-accuracy(predlog1) #Operator 1   
acc\_g2<-accuracy(predlog2) #Operator 2   
acc\_g3<-accuracy(predlog3) #Operator 3   
  
#Modelo Gompertz  
acc\_h1<-accuracy(predgom1) #Operator 1   
acc\_h2<-accuracy(predgom2) #Operator 2   
acc\_h3<-accuracy(predgom3) #Operator 3   
  
#Modelo Fisher-Pry  
acc\_i1<-accuracy(predpry1,tssubs1) #Operator 1   
acc\_i2<-accuracy(predpry2,tssubs2) #Operator 2  
acc\_i3<-accuracy(predpry3,tssubs3) #Operator 3  
  
#Modelo Bass  
acc\_j1<-accuracy(predbas1$Subs,dataVoD1$Subs) #Duda Operator 1  
acc\_j2<-accuracy(predbas2$Subs,dataVoD2$Subs) #Duda Operator 2  
acc\_j3<-accuracy(predbas3$Subs,dataVoD3$Subs) #Duda Operator 3

The performance sets are:

Models<-c("Parabolic","Logistic","Gompertz","Fisher-Pry","Bass")  
  
#Opereator 1  
acce1<-acc\_e1[1,1:5] #Parabolic  
accg1<-acc\_g1[1,1:5] #Logistic  
acch1<-acc\_h1[1,1:5] #Gompertz  
acci1<-acc\_i1[1,1:5] #Fisher-Pry  
accj1<-acc\_j1[1,1:5] #Bass  
acc\_all1b<-round(rbind(acce1,accg1,acch1,acci1,accj1),2)  
performVoD1<-data.frame(Models,acc\_all1b)  
  
#Operator 2  
acce2<-acc\_e1[1,1:5] #Parabolic  
accg2<-acc\_g2[1,1:5]  
acch2<-acc\_h2[1,1:5]  
acci2<-acc\_i2[1,1:5]  
accj2<-acc\_j2[1,1:5]  
acc\_all2b<-round(rbind(acce2,accg2,acch2,acci2,accj2),2)  
performVoD2<-data.frame(Models,acc\_all2b)  
  
#Operator 3  
acce3<-acc\_e1[1,1:5] #Parabolic  
accg3<-acc\_g3[1,1:5]  
acch3<-acc\_h3[1,1:5]  
acci3<-acc\_i3[1,1:5]  
accj3<-acc\_j3[1,1:5]  
acc\_all3b<-round(rbind(acce3,accg3,acch3,acci3,accj3),2)  
performVoD3<-data.frame(Models,acc\_all3b)

## Predictions Reports

#Internet Residential Predictions by service provider  
predVoD1<-data.frame(data\_predlog1,data\_predgom1,data\_pred1c) #Operator 1   
predVoD2<-data.frame(data\_predlog2,data\_predgom2,data\_pred2c) #Operator 2   
predVoD3<-data.frame(data\_predlog3,data\_predgom3,data\_pred3c) #Operator 3

## Forecast Reports

Forecasting for 5 Years Video on Demand

foreVoD1<-data.frame(fore5a,fore6a) #Operator 1  
foreVoD2<-data.frame(fore5b,fore6b) #Operator 2  
foreVoD3<-data.frame(fore5c,fore6c) #Operator 3

# Demand Models for VoIP Subscribers

## Subset data

dataVoIP1<-data.frame(Year=year,Subs=oper1$VoIP1) #Operator 1  
tssubs1<-ts(oper1$VoIP1,start=start,end=end) #Time serie  
dataVoIP2<-data.frame(Year=year,Subs=oper2$VoIP2) #Operator 2  
tssubs2<-ts(oper2$VoIP2,start=start,end=end) #Time serie  
dataVoIP3<-data.frame(Year=year,Subs=oper3$VoIP3) #Operator 3  
tssubs3<-ts(oper3$VoIP3,start=start,end=end) #Time serie

## 4.1.Predicting with Logistic and Gompertz Model VoIP

### Logistic Model

#Operator 1  
alpha1<-tssubs1[hi] +0.5 #upper asymptote (M)  
Y1<-log(alpha1/tssubs1-1) #Transform  
Reglm1<-tslm(Y1~trend) #Lineal Regression  
parmlm1<-as.list(Reglm1$coeff)  
  
beta1<- exp(parmlm1$"(Intercept)") #growth range (a)  
k1<- -parmlm1$trend #growth rate (b)  
fitlog1 <- logistic(1:10, alpha1, beta1, k1)  
predlog1<-forecast(fitlog1,h=seth)  
  
#Operator 2  
alpha2<-tssubs2[hi] +0.5 #upper asymptote (M)  
Y2<-log(alpha2/tssubs2-1) #Transform  
Reglm2<-tslm(Y2~trend) #Lineal Regression  
parmlm2<-as.list(Reglm2$coeff)  
  
beta2<- exp(parmlm2$"(Intercept)") #growth range (a)  
k2<- -parmlm2$trend #growth rate (b)  
fitlog2 <- logistic(1:10, alpha2, beta2, k2)  
predlog2<-forecast(fitlog2,h=seth)  
  
#Operator 3  
alpha3<-tssubs3[hi] +0.5 #upper asymptote (M)  
Y3<-log(alpha3/tssubs3-1) #Transform  
Reglm3<-tslm(Y3~trend) #Lineal Regression  
parmlm3<-as.list(Reglm3$coeff)  
  
beta3<- exp(parmlm3$"(Intercept)") #growth range (a)  
k3<- -parmlm3$trend #growth rate (b)  
fitlog3 <- logistic(1:10, alpha3, beta3, k3)  
predlog3<-forecast(fitlog3,h=seth)  
  
#The predictions using logistic model are:  
set4a<-data.frame(predlog1)  
alog<-set4a$Point.Forecast #Operator 1 predictions  
set4b<-data.frame(predlog2)  
blog<-set4b$Point.Forecast #Operator 2 predictions  
set4c<-data.frame(predlog3)  
clog<-set4c$Point.Forecast #Operator 3 predictions  
  
data\_predlog1<-data.frame(Log1=fitlog1)  
data\_predlog2<-data.frame(Log2=fitlog2)  
data\_predlog3<-data.frame(Log3=fitlog3)

### Gompertz Model

#Operator 1  
alphag1<-tssubs1[hi] +5 #upper asymptote (M)  
Y1g<-log(log(alphag1/tssubs1)) #Transform  
Reglmg1<-tslm(Y1g~trend) #Lineal Regression  
parmglm1<-as.list(Reglmg1$coeff)  
  
betag1<- exp(parmglm1$"(Intercept)") #growth range (a)  
kg1<- -parmglm1$trend #growth rate (b)  
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)  
predgom1<-forecast(fitgom1,h=seth)  
  
#Operator 2  
alphag2<-tssubs2[hi] +5 #upper asymptote (M)  
Y2g<-log(log(alphag2/tssubs2)) #Transform  
Reglmg2<-tslm(Y2g~trend) #Lineal Regression  
parmglm2<-as.list(Reglmg2$coeff)  
  
betag2<- exp(parmglm2$"(Intercept)") #growth range (a)  
kg2<- -parmglm2$trend #growth rate (b)  
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)  
predgom2<-forecast(fitgom2,h=seth)  
  
#Operator 3  
alphag3<-tssubs3[hi] +5 #upper asymptote (M)  
Y3g<-log(log(alphag3/tssubs3)) #Transform  
Reglmg3<-tslm(Y3g~trend) #Lineal Regression  
parmglm3<-as.list(Reglmg3$coeff)  
  
betag3<- exp(parmglm3$"(Intercept)") #growth range (a)  
kg3<- -parmglm3$trend #growth rate (b)  
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)  
predgom3<-forecast(fitgom3,h=seth)

The predictions using gompertz model are:

set5a<-data.frame(predgom1)  
agom<-set5a$Point.Forecast #Operator 1 predictions  
set5b<-data.frame(predgom2)  
bgom<-set5b$Point.Forecast #Operator 2 predictions  
set5c<-data.frame(predgom3)  
cgom<-set5c$Point.Forecast #Operator 3 predictions  
  
data\_predgom1<-data.frame(Gom1=fitgom1)  
data\_predgom2<-data.frame(Gom2=fitgom2)  
data\_predgom3<-data.frame(Gom3=fitgom3)

### Parabolic Model

time<-1:hi  
#Operator 1  
fitpar1=lm(tssubs1 ~ time + I(time^2)) #Model  
predpar1<-predict(fitpar1) #Prediction  
forepar1<-forecast(predpar1,h=seth-3) #Forecast  
#Operator 2  
fitpar2=lm(tssubs2 ~ time + I(time^2)) #Model  
predpar2<-predict(fitpar2) #Prediction  
forepar2<-forecast(predpar2,h=seth-3) #Forecast  
#Operator 3  
fitpar3=lm(tssubs3 ~ time + I(time^2)) #Model   
predpar3<-predict(fitpar3) #Prediction  
forepar3<-forecast(predpar3,h=seth-3) #Forecast

### Forecasting for 5 years

fore7a<-data.frame(Fore\_Log1=alog[1:5],Fore\_Gom1=agom[1:5],Fore\_Par1=forepar1)  
fore7b<-data.frame(Fore\_Log2=blog[1:5],Fore\_Gom2=bgom[1:5],Fore\_Par1=forepar1)  
fore7c<-data.frame(Fore\_Log3=clog[1:5],Fore\_Gom3=cgom[1:5],Fore\_Par1=forepar1)

## Predicting with Fisher Pry

Model applied When substitution is driven by superior technology. The new product or service presents some technological advantage over the old one.

#Operator 1  
L1<-tssubs1[hi]+5 #upper asymptote (L)  
transf1<-log((L1-tssubs1)/tssubs1) #transform  
  
fitpry1<-tslm(transf1~trend) #model  
set5a<-fitpry1$fitted.values  
predpry1<-L1/(1+exp(set5a)) #Prediction  
forepry1<-forecast(predpry1,h=seth) #Forecast  
  
#Operator 2  
L2<-tssubs2[hi]+5 #upper asymptote (L)  
transf2<-log((L2-tssubs2)/tssubs2) #transform  
  
fitpry2<-tslm(transf2~trend) #model  
set5b<-fitpry2$fitted.values  
predpry2<-L2/(1+exp(set5b)) #Prediction  
forepry2<-forecast(predpry2,h=seth) #Forecast  
  
#Operator 3  
L3<-tssubs3[hi]+5 #upper asymptote (L)  
transf3<-log((L3-tssubs3)/tssubs3) #transform  
  
fitpry3<-tslm(transf3~trend) #model  
set5c<-fitpry3$fitted.values  
predpry3<-L3/(1+exp(set5c)) #Prediction  
forepry3<-forecast(predpry3,h=seth) #Forecast

## 12. Bass Model

**m** Total number of potential buyers of the new product **p** The coefficient of innovation **q** The coefficient of imitation

#Operator1  
setbas1<-subset(dataVoIP1,Subs>=0.11)  
setbas2<-subset(dataVoIP1,Subs<0.11)  
demand1<-tssubs1[(tssubs1)>=0.11]  
time<-1:length(demand1)  
Tdelt <- time #Accuracy, size predictions  
  
Bass.nls <- nls(demand1 ~ M \* (((P + Q)^2/P) \* exp(-(P + Q) \* time))/(1 + (Q/P)   
 \*exp(-(P + Q) \* time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))  
Bcoef <- coef(Bass.nls) # get coefficient operator 1  
m <- Bcoef[1]  
p <- Bcoef[2]  
q <- Bcoef[3]  
ngete <- exp(-(p + q) \* Tdelt) #Setting the starting values for M to the Subs  
  
fitbas1 <- m \* ((p + q)^2/p) \* ngete/(1 + (q/p) \* ngete)^2 #Model  
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas1) #Prediction  
x<-nrow(setbas2)  
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x\*0))  
predbas1<-rbind(cero,setbas3)  
forebas1<-forecast(predbas1$Subs,h=seth) #Forecast  
  
#Operator2  
setbas1<-subset(dataVoIP2,Subs>=0.11)  
setbas2<-subset(dataVoIP2,Subs<0.11)  
demand2<-tssubs2[(tssubs2)>=0.11]  
time<-1:length(demand2)  
Tdelt <- time #Accuracy, size predictions  
  
Bass.nls <- nls(demand2 ~ M \* (((P + Q)^2/P) \* exp(-(P + Q) \* time))/(1 + (Q/P)   
 \*exp(-(P + Q) \* time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))  
Bcoef <- coef(Bass.nls) # get coefficient operator 1  
m <- Bcoef[1]  
p <- Bcoef[2]  
q <- Bcoef[3]  
ngete <- exp(-(p + q) \* Tdelt) #Setting the starting values for M to the Subs  
  
fitbas2 <- m \* ((p + q)^2/p) \* ngete/(1 + (q/p) \* ngete)^2 #Model  
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas2) #Prediction  
x<-nrow(setbas2)  
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x\*0))  
predbas2<-rbind(cero,setbas3)  
forebas2<-forecast(predbas2$Subs,h=seth) #Forecast  
  
#Operator3  
setbas1<-subset(dataVoIP3,Subs>=0.11)  
setbas2<-subset(dataVoIP3,Subs<0.11)  
demand3<-tssubs3[(tssubs3)>=0.11]  
time<-1:length(demand3)  
Tdelt <- time #Accuracy, size predictions  
  
Bass.nls <- nls(demand3 ~ M \* (((P + Q)^2/P) \* exp(-(P + Q) \* time))/(1 + (Q/P)   
 \*exp(-(P + Q) \* time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))  
Bcoef <- coef(Bass.nls) # get coefficient operator 1  
m <- Bcoef[1]  
p <- Bcoef[2]  
q <- Bcoef[3]  
ngete <- exp(-(p + q) \* Tdelt) #Setting the starting values for M to the Subs  
  
fitbas3 <- m \* ((p + q)^2/p) \* ngete/(1 + (q/p) \* ngete)^2 #Model  
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas3) #Prediction  
x<-nrow(setbas2)  
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x\*0))  
predbas3<-rbind(cero,setbas3)  
forebas3<-forecast(predbas3$Subs,h=seth) #Forecast

The predictions using Bass and Fisher Pry model are:

set6a<-data.frame(forepry1)  
apry<-set6a$Point.Forecast #Operator 1 predictions  
set6b<-data.frame(forepry2)  
bpry<-set6b$Point.Forecast #Operator 2 predictions  
set6c<-data.frame(forepry3)  
cpry<-set6c$Point.Forecast #Operator 3 predictions  
  
set7a<-data.frame(forebas1)  
abas<-set7a$Point.Forecast #Operator 1 predictions  
set7b<-data.frame(forebas2)  
bbas<-set7b$Point.Forecast #Operator 2 predictions  
set7c<-data.frame(forebas3)  
cbas<-set7c$Point.Forecast #Operator 3 predictions  
  
data\_pred1c<-data.frame(Pry1=predpry1,Bass1=predbas1$Subs)  
data\_pred2c<-data.frame(Pry2=predpry2,Bass2=predbas2$Subs)  
data\_pred3c<-data.frame(Pry3=predpry3,Bass3=predbas3$Subs)

## Forecasting for 5 years

fore8a<-data.frame(Fore\_Pry1=apry[1:5],Fore\_Bas1=abas[1:5])  
fore8b<-data.frame(Fore\_Pry2=bpry[1:5],Fore\_Bas2=bbas[1:5])  
fore8c<-data.frame(Fore\_Pry3=cpry[1:5],Fore\_Bas3=cbas[1:5])

## 13.Performance Models for VoIP

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error **(MAE)**: Mean Absolute Error **(MPE)**: Mean Porcentual Error **(MAPE)**: Mean Absolute Porcentual Error

#Modelo Parabólico  
acc\_e1<-accuracy(predpar1,tssubs1) #Operator 1  
acc\_e2<-accuracy(predpar2,tssubs2) #Operator 2  
acc\_e3<-accuracy(predpar3,tssubs3) #Operator 3  
  
#Modelo Logístico  
acc\_g1<-accuracy(predlog1) #Operator 1   
acc\_g2<-accuracy(predlog2) #Operator 2   
acc\_g3<-accuracy(predlog3) #Operator 3   
  
#Modelo Gompertz  
acc\_h1<-accuracy(predgom1) #Operator 1   
acc\_h2<-accuracy(predgom2) #Operator 2   
acc\_h3<-accuracy(predgom3) #Operator 3   
  
#Modelo Fisher-Pry  
acc\_i1<-accuracy(predpry1,tssubs1) #Operator 1   
acc\_i2<-accuracy(predpry2,tssubs2) #Operator 2  
acc\_i3<-accuracy(predpry3,tssubs3) #Operator 3  
  
#Modelo Bass  
acc\_j1<-accuracy(predbas1$Subs,dataVoIP1$Subs) #Duda Operator 1  
acc\_j2<-accuracy(predbas2$Subs,dataVoIP2$Subs) #Duda Operator 2  
acc\_j3<-accuracy(predbas3$Subs,dataVoIP3$Subs) #Duda Operator 3

The performance sets are:

Models<-c("Parabolic","Logistic","Gompertz","Fisher-Pry","Bass")  
  
#Opereator 1  
acce1<-acc\_e1[1,1:5] #Parabolic  
accg1<-acc\_g1[1,1:5] #Logistic  
acch1<-acc\_h1[1,1:5] #Gompertz  
acci1<-acc\_i1[1,1:5] #Fisher-Pry  
accj1<-acc\_j1[1,1:5] #Bass  
acc\_all1b<-round(rbind(acce1,accg1,acch1,acci1,accj1),2)  
performVoIP1<-data.frame(Models,acc\_all1b)  
  
#Operator 2  
acce2<-acc\_e1[1,1:5] #Parabolic  
accg2<-acc\_g2[1,1:5]  
acch2<-acc\_h2[1,1:5]  
acci2<-acc\_i2[1,1:5]  
accj2<-acc\_j2[1,1:5]  
acc\_all2b<-round(rbind(acce2,accg2,acch2,acci2,accj2),2)  
performVoIP2<-data.frame(Models,acc\_all2b)  
  
#Operator 3  
acce3<-acc\_e1[1,1:5] #Parabolic  
accg3<-acc\_g3[1,1:5]  
acch3<-acc\_h3[1,1:5]  
acci3<-acc\_i3[1,1:5]  
accj3<-acc\_j3[1,1:5]  
acc\_all3b<-round(rbind(acce3,accg3,acch3,acci3,accj3),2)  
performVoIP3<-data.frame(Models,acc\_all3b)

## Predictions Reports

VoIP Predictions by service provider

predVoIP1<-data.frame(data\_predlog1,data\_predgom1,data\_pred1c) #Operator 1   
predVoIP2<-data.frame(data\_predlog2,data\_predgom2,data\_pred2c) #Operator 2   
predVoIP3<-data.frame(data\_predlog3,data\_predgom3,data\_pred3c) #Operator 3

## Forecast Reports

Forecasting for 5 Years Video on Demand

foreVoIP1<-data.frame(fore7a,fore8a) #Operator 1  
foreVoIP2<-data.frame(fore7b,fore8b) #Operator 2  
foreVoIP3<-data.frame(fore7c,fore8c) #Operator 3

# Predictions, Forecast and Performance Reports

## Predictions Report

predIRes<-round(data.frame(predIRes1,predIRes2,predIRes3),2)  
predIBus<-round(data.frame(predIBus1,predIBus2,predIBus3),2)  
predVoD<-round(data.frame(predVoD1,predVoD2,predVoD3),2)  
predVoIP<-round(data.frame(predVoIP1,predVoIP2,predVoIP3),2)  
  
predict<-data.frame(Res=predIRes,VoD=predVoD,VoIP=predVoIP,Bus=predIBus)  
predict

## Res.Lin1 Res.Par1 Res.Exp1 Res.Log1 Res.Gom1 Res.Lin2 Res.Par2 Res.Exp2  
## 1 -0.12 -0.05 0.00 0.00 0.00 21.49 21.47 21.66  
## 2 -0.02 -0.01 0.01 0.01 0.01 22.52 22.50 22.56  
## 3 0.08 0.05 0.02 0.02 0.02 23.55 23.54 23.49  
## 4 0.19 0.14 0.04 0.04 0.06 24.59 24.58 24.46  
## 5 0.29 0.24 0.07 0.09 0.13 25.62 25.63 25.48  
## 6 0.39 0.37 0.15 0.20 0.25 26.65 26.68 26.53  
## 7 0.49 0.52 0.31 0.40 0.43 27.68 27.74 27.63  
## 8 0.60 0.69 0.65 0.70 0.67 28.71 28.81 28.78  
## 9 0.70 0.88 1.33 1.02 0.97 29.75 29.88 29.97  
## 10 0.80 1.10 2.73 1.28 1.32 30.78 30.96 31.21  
## Res.Log2 Res.Gom2 Res.Lin3 Res.Par3 Res.Exp3 Res.Log3 Res.Gom3 VoD.Log1  
## 1 18.86 20.69 2.08 2.32 3.28 2.01 1.96 0.00  
## 2 21.25 22.18 3.91 3.91 4.10 3.27 3.48 0.00  
## 3 23.38 23.58 5.75 5.62 5.13 5.10 5.44 0.00  
## 4 25.20 24.86 7.59 7.44 6.42 7.51 7.69 0.00  
## 5 26.68 26.05 9.42 9.37 8.02 10.30 10.06 0.00  
## 6 27.86 27.13 11.26 11.41 10.03 13.10 12.37 0.00  
## 7 28.78 28.11 13.09 13.57 12.55 15.53 14.53 0.01  
## 8 29.47 28.99 14.93 15.84 15.69 17.38 16.45 0.02  
## 9 29.99 29.78 16.76 18.22 19.62 18.65 18.11 0.06  
## 10 30.37 30.50 18.60 20.71 24.53 19.47 19.51 0.13  
## VoD.Gom1 VoD.Pry1 VoD.Bass1 VoD.Log2 VoD.Gom2 VoD.Pry2 VoD.Bass2  
## 1 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 2 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 3 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 4 0.00 0.00 0.01 0.00 0.00 0.00 0.00  
## 5 0.00 0.00 0.01 0.00 0.01 0.00 0.00  
## 6 0.00 0.00 0.02 0.00 0.05 0.00 0.00  
## 7 0.01 0.01 0.02 0.03 0.19 0.02 0.80  
## 8 0.02 0.02 0.02 0.28 0.51 0.17 1.01  
## 9 0.03 0.06 0.02 1.14 1.03 1.21 1.19  
## 10 0.05 0.16 0.01 1.70 1.72 4.20 1.30  
## VoD.Log3 VoD.Gom3 VoD.Pry3 VoD.Bass3 VoIP.Log1 VoIP.Gom1 VoIP.Pry1  
## 1 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 2 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 3 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 4 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 5 0.00 0.01 0.00 0.00 0.00 0.01 0.00  
## 6 0.00 0.05 0.00 0.00 0.00 0.05 0.00  
## 7 0.03 0.19 0.02 0.80 0.03 0.19 0.02  
## 8 0.28 0.51 0.17 1.01 0.28 0.51 0.17  
## 9 1.14 1.03 1.21 1.19 1.14 1.03 1.21  
## 10 1.70 1.72 4.20 1.30 1.70 1.72 4.20  
## VoIP.Bass1 VoIP.Log2 VoIP.Gom2 VoIP.Pry2 VoIP.Bass2 VoIP.Log3 VoIP.Gom3  
## 1 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 2 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 3 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 4 0.00 0.00 0.00 0.00 0.00 0.00 0.00  
## 5 0.00 0.00 0.01 0.00 0.00 0.00 0.01  
## 6 0.00 0.00 0.05 0.00 0.00 0.00 0.05  
## 7 0.80 0.03 0.19 0.02 0.80 0.03 0.19  
## 8 1.01 0.28 0.51 0.17 1.01 0.28 0.51  
## 9 1.19 1.14 1.03 1.21 1.19 1.14 1.03  
## 10 1.30 1.70 1.72 4.20 1.30 1.70 1.72  
## VoIP.Pry3 VoIP.Bass3 Bus.Lin1 Bus.Par1 Bus.Exp1 Bus.Log1 Bus.Gom1  
## 1 0.00 0.00 0.01 0.05 0.04 0.03 0.03  
## 2 0.00 0.00 0.05 0.04 0.05 0.05 0.05  
## 3 0.00 0.00 0.09 0.06 0.07 0.07 0.08  
## 4 0.00 0.00 0.12 0.09 0.10 0.11 0.12  
## 5 0.00 0.00 0.16 0.15 0.15 0.16 0.17  
## 6 0.00 0.00 0.20 0.22 0.21 0.23 0.24  
## 7 0.02 0.80 0.24 0.32 0.29 0.32 0.32  
## 8 0.17 1.01 0.28 0.44 0.40 0.43 0.43  
## 9 1.21 1.19 0.31 0.58 0.57 0.56 0.55  
## 10 4.20 1.30 0.35 0.75 0.79 0.69 0.69  
## Bus.Lin2 Bus.Par2 Bus.Exp2 Bus.Log2 Bus.Gom2 Bus.Lin3 Bus.Par3 Bus.Exp3  
## 1 0.37 0.38 0.47 0.41 0.44 0.37 0.38 0.47  
## 2 0.54 0.54 0.55 0.53 0.55 0.54 0.54 0.55  
## 3 0.70 0.70 0.65 0.67 0.67 0.70 0.70 0.65  
## 4 0.86 0.86 0.77 0.83 0.81 0.86 0.86 0.77  
## 5 1.02 1.02 0.91 1.00 0.97 1.02 1.02 0.91  
## 6 1.18 1.18 1.07 1.18 1.13 1.18 1.18 1.07  
## 7 1.34 1.34 1.27 1.36 1.31 1.34 1.34 1.27  
## 8 1.50 1.50 1.50 1.53 1.50 1.50 1.50 1.50  
## 9 1.66 1.67 1.77 1.68 1.70 1.66 1.67 1.77  
## 10 1.82 1.83 2.08 1.81 1.90 1.82 1.83 2.08  
## Bus.Log3 Bus.Gom3  
## 1 0.41 0.44  
## 2 0.53 0.55  
## 3 0.67 0.67  
## 4 0.83 0.81  
## 5 1.00 0.97  
## 6 1.18 1.13  
## 7 1.36 1.31  
## 8 1.53 1.50  
## 9 1.68 1.70  
## 10 1.81 1.90

#write.csv2(predict,"Predictions\_Report.csv")

## Forecast Report

foreIRes<-round(data.frame(foreIRes1,foreIRes2,foreIRes3),2)  
foreIBus<-round(data.frame(foreIBus1,foreIBus2,foreIBus3),2)  
foreVoD<-round(data.frame(foreVoD1,foreVoD2,foreVoD3),2)  
foreVoIP<-round(data.frame(foreVoIP1,foreVoIP2,foreVoIP3),2)  
  
forecast<-data.frame(Res=foreIRes,VoD=foreVoD,VoIP=foreVoIP,Bus=foreIBus)  
forecast

## Res.Year Res.Fore\_Lin1 Res.Fore\_Par1 Res.Fore\_Exp1 Res.Fore\_Log1  
## 11 2017 0.90 1.23 2.73 1.28  
## 12 2018 1.00 1.35 2.73 1.28  
## 13 2019 1.11 1.48 2.73 1.28  
## 14 2020 1.21 1.61 2.73 1.28  
## 15 2021 1.31 1.74 2.73 1.28  
## Res.Fore\_Gom1 Res.Fore\_Lin2 Res.Fore\_Par2 Res.Fore\_Exp2 Res.Fore\_Log2  
## 11 1.32 31.81 32.04 32.46 30.72  
## 12 1.32 32.84 33.12 33.70 31.01  
## 13 1.32 33.88 34.20 34.94 31.25  
## 14 1.32 34.91 35.28 36.18 31.45  
## 15 1.32 35.94 36.36 37.42 31.62  
## Res.Fore\_Gom1.1 Res.Fore\_Lin3 Res.Fore\_Par3 Res.Fore\_Exp3 Res.Fore\_Log3  
## 11 31.15 20.44 23.20 29.43 20.29  
## 12 31.74 22.27 25.69 34.34 21.11  
## 13 32.29 24.11 28.19 39.26 21.93  
## 14 32.78 25.94 30.68 44.17 22.75  
## 15 33.24 27.78 33.17 49.08 23.57  
## Res.Fore\_Gom1.2 VoD.Fore\_Log1 VoD.Fore\_Gom1  
## 11 20.92 0.13 0.07  
## 12 22.32 0.13 0.09  
## 13 23.72 0.13 0.12  
## 14 25.12 0.13 0.14  
## 15 26.52 0.13 0.16  
## VoD.Fore\_Par1.Point.Forecast VoD.Fore\_Par1.Lo.80 VoD.Fore\_Par1.Hi.80  
## 11 0.01 0.01 0.01  
## 12 0.01 0.01 0.02  
## 13 0.01 0.01 0.02  
## 14 0.01 0.01 0.02  
## 15 0.01 0.00 0.02  
## VoD.Fore\_Par1.Lo.95 VoD.Fore\_Par1.Hi.95 VoD.Fore\_Pry1 VoD.Fore\_Bas1  
## 11 0.01 0.02 0.16 0.01  
## 12 0.01 0.02 0.16 0.01  
## 13 0.01 0.02 0.16 0.02  
## 14 0.00 0.02 0.16 0.02  
## 15 0.00 0.02 0.16 0.02  
## VoD.Fore\_Log2 VoD.Fore\_Gom2 VoD.Fore\_Par2.Point.Forecast  
## 11 1.7 0 1.48  
## 12 1.7 0 1.48  
## 13 1.7 0 1.48  
## 14 1.7 0 1.48  
## 15 1.7 0 1.48  
## VoD.Fore\_Par2.Lo.80 VoD.Fore\_Par2.Hi.80 VoD.Fore\_Par2.Lo.95  
## 11 1.23 1.74 1.10  
## 12 1.12 1.84 0.93  
## 13 1.04 1.92 0.81  
## 14 0.98 1.99 0.71  
## 15 0.92 2.05 0.61  
## VoD.Fore\_Par2.Hi.95 VoD.Fore\_Pry2 VoD.Fore\_Bas2 VoD.Fore\_Log3  
## 11 1.87 4.13 1.3 1.7  
## 12 2.03 4.13 1.3 1.7  
## 13 2.16 4.13 1.3 1.7  
## 14 2.26 4.13 1.3 1.7  
## 15 2.35 4.13 1.3 1.7  
## VoD.Fore\_Gom3 VoD.Fore\_Par3.Point.Forecast VoD.Fore\_Par3.Lo.80  
## 11 0 1.48 1.23  
## 12 0 1.48 1.12  
## 13 0 1.48 1.04  
## 14 0 1.48 0.98  
## 15 0 1.48 0.92  
## VoD.Fore\_Par3.Hi.80 VoD.Fore\_Par3.Lo.95 VoD.Fore\_Par3.Hi.95  
## 11 1.74 1.10 1.87  
## 12 1.84 0.93 2.03  
## 13 1.92 0.81 2.16  
## 14 1.99 0.71 2.26  
## 15 2.05 0.61 2.35  
## VoD.Fore\_Pry3 VoD.Fore\_Bas3 VoIP.Fore\_Log1 VoIP.Fore\_Gom1  
## 11 4.13 1.3 1.7 0  
## 12 4.13 1.3 1.7 0  
## 13 4.13 1.3 1.7 0  
## 14 4.13 1.3 1.7 0  
## 15 4.13 1.3 1.7 0  
## VoIP.Fore\_Par1.Point.Forecast VoIP.Fore\_Par1.Lo.80 VoIP.Fore\_Par1.Hi.80  
## 11 1.48 1.23 1.74  
## 12 1.48 1.12 1.84  
## 13 1.48 1.04 1.92  
## 14 1.48 0.98 1.99  
## 15 1.48 0.92 2.05  
## VoIP.Fore\_Par1.Lo.95 VoIP.Fore\_Par1.Hi.95 VoIP.Fore\_Pry1 VoIP.Fore\_Bas1  
## 11 1.10 1.87 4.13 1.3  
## 12 0.93 2.03 4.13 1.3  
## 13 0.81 2.16 4.13 1.3  
## 14 0.71 2.26 4.13 1.3  
## 15 0.61 2.35 4.13 1.3  
## VoIP.Fore\_Log2 VoIP.Fore\_Gom2 VoIP.Fore\_Par1.Point.Forecast.1  
## 11 1.7 0 1.48  
## 12 1.7 0 1.48  
## 13 1.7 0 1.48  
## 14 1.7 0 1.48  
## 15 1.7 0 1.48  
## VoIP.Fore\_Par1.Lo.80.1 VoIP.Fore\_Par1.Hi.80.1 VoIP.Fore\_Par1.Lo.95.1  
## 11 1.23 1.74 1.10  
## 12 1.12 1.84 0.93  
## 13 1.04 1.92 0.81  
## 14 0.98 1.99 0.71  
## 15 0.92 2.05 0.61  
## VoIP.Fore\_Par1.Hi.95.1 VoIP.Fore\_Pry2 VoIP.Fore\_Bas2 VoIP.Fore\_Log3  
## 11 1.87 4.13 1.3 1.7  
## 12 2.03 4.13 1.3 1.7  
## 13 2.16 4.13 1.3 1.7  
## 14 2.26 4.13 1.3 1.7  
## 15 2.35 4.13 1.3 1.7  
## VoIP.Fore\_Gom3 VoIP.Fore\_Par1.Point.Forecast.2 VoIP.Fore\_Par1.Lo.80.2  
## 11 0 1.48 1.23  
## 12 0 1.48 1.12  
## 13 0 1.48 1.04  
## 14 0 1.48 0.98  
## 15 0 1.48 0.92  
## VoIP.Fore\_Par1.Hi.80.2 VoIP.Fore\_Par1.Lo.95.2 VoIP.Fore\_Par1.Hi.95.2  
## 11 1.74 1.10 1.87  
## 12 1.84 0.93 2.03  
## 13 1.92 0.81 2.16  
## 14 1.99 0.71 2.26  
## 15 2.05 0.61 2.35  
## VoIP.Fore\_Pry3 VoIP.Fore\_Bas3 Bus.Year Bus.Fore\_Lin1 Bus.Fore\_Par1  
## 11 4.13 1.3 2017 0.39 0.75  
## 12 4.13 1.3 2018 0.43 0.75  
## 13 4.13 1.3 2019 0.47 0.75  
## 14 4.13 1.3 2020 0.50 0.75  
## 15 4.13 1.3 2021 0.54 0.75  
## Bus.Fore\_Exp1 Bus.Fore\_Log1 Bus.Fore\_Gom1 Bus.Fore\_Lin2 Bus.Fore\_Par2  
## 11 0.79 0.81 0.69 1.98 1.99  
## 12 0.79 0.92 0.69 2.14 2.15  
## 13 0.79 1.03 0.69 2.30 2.31  
## 14 0.79 1.13 0.69 2.46 2.47  
## 15 0.79 1.24 0.69 2.62 2.63  
## Bus.Fore\_Exp2 Bus.Fore\_Log2 Bus.Fore\_Gom1.1 Bus.Fore\_Lin3 Bus.Fore\_Par3  
## 11 2.40 1.97 2.11 1.98 1.99  
## 12 2.72 2.12 2.31 2.14 2.15  
## 13 3.04 2.28 2.51 2.30 2.31  
## 14 3.36 2.43 2.72 2.46 2.47  
## 15 3.67 2.59 2.92 2.62 2.63  
## Bus.Fore\_Exp3 Bus.Fore\_Log3 Bus.Fore\_Gom1.2  
## 11 2.40 1.97 2.11  
## 12 2.72 2.12 2.31  
## 13 3.04 2.28 2.51  
## 14 3.36 2.43 2.72  
## 15 3.67 2.59 2.92

#write.csv2(forecast,"Forecasting\_Report.csv")

## Performance Report

performIRes<-data.frame(performIRes1,performIRes2[2:6],performIRes3[2:6]) #Internet Residential  
performIBus<-data.frame(performIBus1,performIBus2[2:6],performIBus3[2:6]) #Internet Bussines  
performVoD<-data.frame(performVoD1,performVoD2[2:6],performVoD3[2:6]) #Video on Demand  
performVoIP<-data.frame(performVoIP1,performVoIP2[2:6],performVoIP3[2:6]) #Voice over IP  
  
perform<-data.frame(Res=performIRes,VoD=performVoD,VoIP=performVoIP)#,performIBus)  
perform

## Res.Models Res.ME Res.RMSE Res.MAE Res.MPE Res.MAPE Res.ME.1  
## accd1 Linear 0.00 0.10 0.09 389.34 787.25 0.00  
## acce1 Parabolic 0.00 0.06 0.05 82.09 254.52 0.00  
## accf1 Exponential 0.27 0.51 0.27 50.12 50.12 0.27  
## accg1 Logistic 0.13 0.18 0.13 46.15 46.15 0.13  
## acch1 Gompertz 0.13 0.18 0.13 48.66 48.66 0.13  
## Res.RMSE.1 Res.MAE.1 Res.MPE.1 Res.MAPE.1 Res.ME.2 Res.RMSE.2  
## accd1 0.36 0.31 -0.03 1.27 0.00 0.63  
## acce1 0.06 0.05 82.09 254.52 0.00 0.06  
## accf1 0.51 0.27 50.12 50.12 0.27 0.51  
## accg1 0.18 0.13 46.15 46.15 0.13 0.18  
## acch1 0.18 0.13 48.66 48.66 0.13 0.18  
## Res.MAE.2 Res.MPE.2 Res.MAPE.2 VoD.Models VoD.ME VoD.RMSE VoD.MAE  
## accd1 0.48 -0.30 11.74 Parabolic 0.00 0.00 0.00  
## acce1 0.05 82.09 254.52 Logistic 0.01 0.03 0.01  
## accf1 0.27 50.12 50.12 Gompertz 0.00 0.00 0.00  
## accg1 0.13 46.15 46.15 Fisher-Pry -0.01 0.05 0.02  
## acch1 0.13 48.66 48.66 Bass 0.00 0.00 0.00  
## VoD.MPE VoD.MAPE VoD.ME.1 VoD.RMSE.1 VoD.MAE.1 VoD.MPE.1  
## accd1 22161.44 55282.03 0.00 0.00 0.00 22161.44  
## acce1 61.56 61.56 0.17 0.33 0.17 81.98  
## accf1 25.72 25.80 0.35 0.66 0.35 93.96  
## accg1 -789.25 873.86 -0.12 0.98 0.46 -3382.14  
## acch1 -38430.40 38441.36 0.01 0.03 0.01 60.00  
## VoD.MAPE.1 VoD.ME.2 VoD.RMSE.2 VoD.MAE.2 VoD.MPE.2 VoD.MAPE.2  
## accd1 55282.03 0.00 0.00 0.00 22161.44 55282.03  
## acce1 81.98 0.17 0.33 0.17 81.98 81.98  
## accf1 93.96 0.35 0.66 0.35 93.96 93.96  
## accg1 3466.14 -0.12 0.98 0.46 -3382.14 3466.14  
## acch1 60.21 0.01 0.03 0.01 60.00 60.21  
## VoIP.Models VoIP.ME VoIP.RMSE VoIP.MAE VoIP.MPE VoIP.MAPE  
## accd1 Parabolic 0.00 0.15 0.12 -1090921.68 3030325.27  
## acce1 Logistic 0.17 0.33 0.17 81.98 81.98  
## accf1 Gompertz 0.35 0.66 0.35 93.96 93.96  
## accg1 Fisher-Pry -0.12 0.98 0.46 -3382.14 3466.14  
## acch1 Bass 0.01 0.03 0.01 60.00 60.21  
## VoIP.ME.1 VoIP.RMSE.1 VoIP.MAE.1 VoIP.MPE.1 VoIP.MAPE.1 VoIP.ME.2  
## accd1 0.00 0.15 0.12 -1090921.68 3030325.27 0.00  
## acce1 0.17 0.33 0.17 81.98 81.98 0.17  
## accf1 0.35 0.66 0.35 93.96 93.96 0.35  
## accg1 -0.12 0.98 0.46 -3382.14 3466.14 -0.12  
## acch1 0.01 0.03 0.01 60.00 60.21 0.01  
## VoIP.RMSE.2 VoIP.MAE.2 VoIP.MPE.2 VoIP.MAPE.2  
## accd1 0.15 0.12 -1090921.68 3030325.27  
## acce1 0.33 0.17 81.98 81.98  
## accf1 0.66 0.35 93.96 93.96  
## accg1 0.98 0.46 -3382.14 3466.14  
## acch1 0.03 0.01 60.00 60.21

#write.csv2(perform,"Performance\_Report.csv")