DATA624-HW2-Forecasting

FPP-Hyndman exercises $3.1,\,3.2,\,3.3$ and 3.8

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library(fpp2)

```
## Loading required package: ggplot2
## Loading required package: forecast
## Registered S3 method overwritten by 'xts':
##
    method
               from
##
    as.zoo.xts zoo
## Registered S3 method overwritten by 'quantmod':
##
    method
                     from
   as.zoo.data.frame zoo
##
## Registered S3 methods overwritten by 'forecast':
    method
##
                      from
##
   fitted.fracdiff fracdiff
    residuals.fracdiff fracdiff
##
## Loading required package: fma
## Loading required package: expsmooth
```

Homework 2 - Forecasting

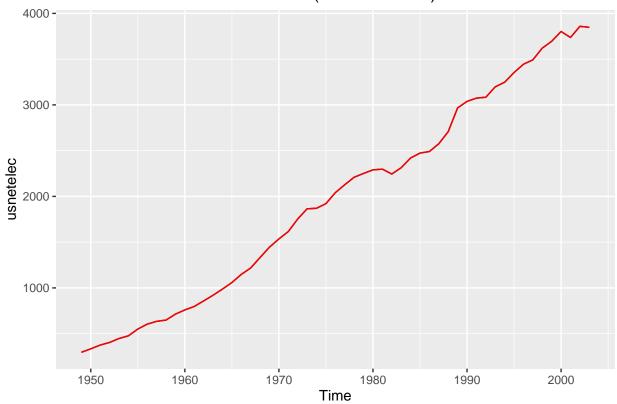
Do exercises 3.1, 3.2, 3.3 and 3.8 from the online Hyndman book. Please submit both your Rpubs link as well as attach the .rmd file with your code.

3.1 For the following series, find an appropriate Box-Cox transformation in order to stabilise the variance.

usnetelec: Annual US net electricity generation (billion kwh) for 1949-2003

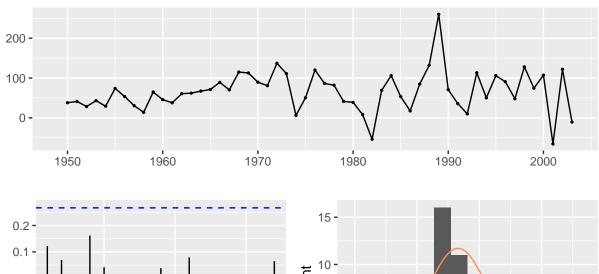
```
### plot raw data series
autoplot(usnetelec) +
   ggtitle(paste("usnetelec (untransformed)")) +
   theme(plot.title = element_text(hjust = 0.5))+
   geom_line(color="red")
```

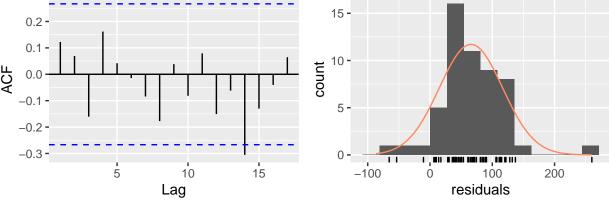
usnetelec (untransformed)



usnetelec.ljung <- checkresiduals(naive(usnetelec))</pre>

Residuals from Naive method





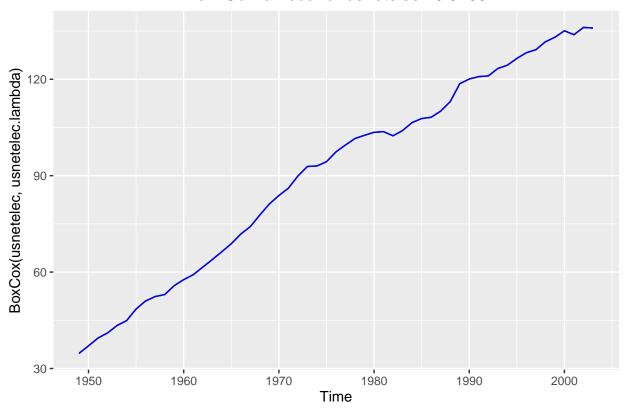
```
##
## Ljung-Box test
##
## data: Residuals from Naive method
## Q* = 7.4406, df = 10, p-value = 0.6833
##
## Model df: 0. Total lags used: 10
```

[1] "Because the p-value on the Ljung-Box test is large, \n the Box-Cox transform is not nece

```
### Box-Cox transform
usnetelec.lambda <- BoxCox.lambda(usnetelec)
### Plot transformed series
#print(paste("Box-Cox lambda for usnetelec: ", round(usnetelec.lambda,3)))
autoplot(BoxCox(usnetelec, usnetelec.lambda)) +
    ggtitle(paste("Box-Cox lambda for usnetelec: ", round(usnetelec.lambda,4))) +</pre>
```

```
theme(plot.title = element_text(hjust = 0.5))+
geom_line(color="blue")
```

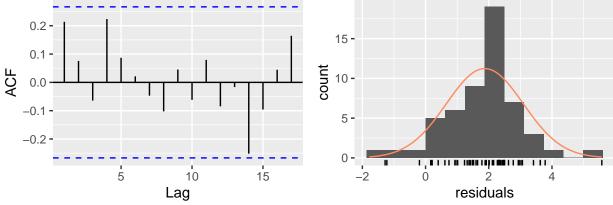
Box-Cox lambda for usnetelec: 0.5168



usnetelec.xform.ljung <- checkresiduals(naive(BoxCox(usnetelec, usnetelec.lambda)))</pre>

Residuals from Naive method





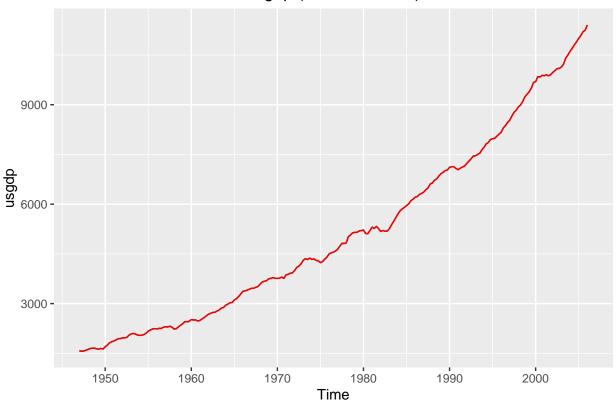
```
##
## Ljung-Box test
##
## data: Residuals from Naive method
## Q* = 7.9451, df = 10, p-value = 0.6342
##
## Model df: 0. Total lags used: 10
```

#usnetelec.xform.ljung

usgdp: Quarterly US GDP. 1947:1 - 2006.1

```
### plot raw data series
autoplot(usgdp) +
   ggtitle(paste("usgdp (untransformed)")) +
   theme(plot.title = element_text(hjust = 0.5))+
   geom_line(color="red")
```

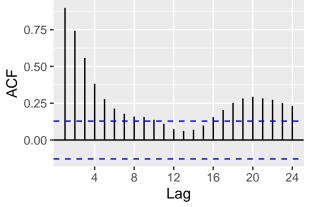
usgdp (untransformed)

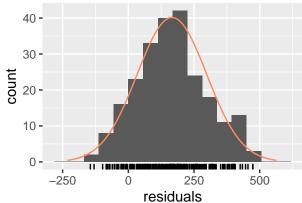


```
usgdp.ljung <- checkresiduals(snaive(usgdp))</pre>
```

Residuals from Seasonal naive method







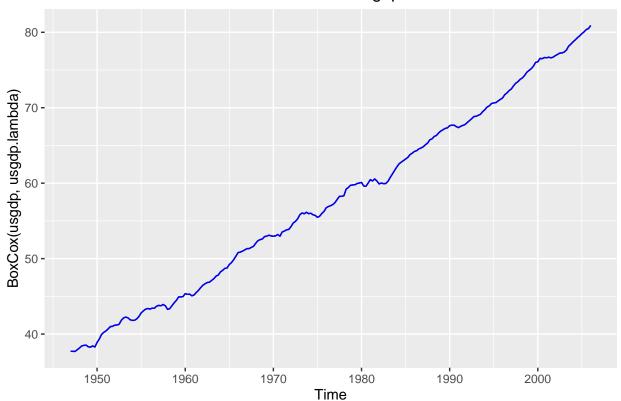
[1] "Because the p-value on the Ljung-Box test is small, \n

we'll try Box-Cox transform to

```
### Box-Cox transform
usgdp.lambda <- BoxCox.lambda(usgdp)
### Plot transformed series
#print(paste("Box-Cox lambda for usgdp: ", round(usgdp.lambda,3)))
autoplot(BoxCox(usgdp, usgdp.lambda)) +
    ggtitle(paste("Box-Cox lambda for usgdp: ", round(usgdp.lambda,4))) +</pre>
```

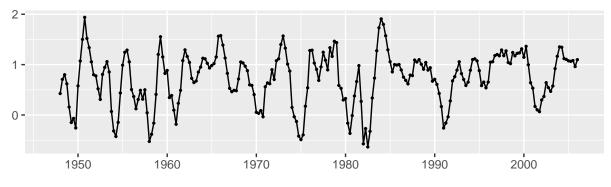
```
theme(plot.title = element_text(hjust = 0.5))+
geom_line(color="blue")
```

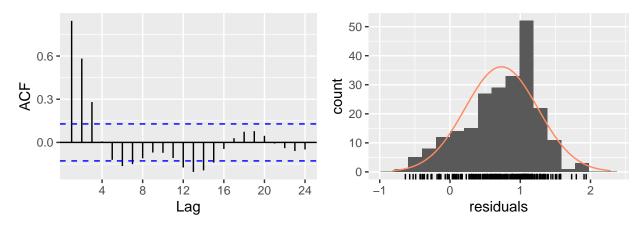
Box-Cox lambda for usgdp: 0.3664



usgdp.xform.ljung <- checkresiduals(snaive(BoxCox(usgdp, usgdp.lambda)))</pre>

Residuals from Seasonal naive method





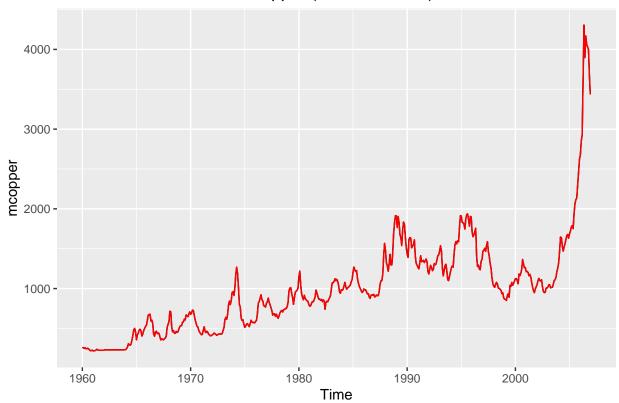
```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 285.76, df = 8, p-value < 0.0000000000000000022
##
## Model df: 0. Total lags used: 8</pre>
```

#usgdp.xform.ljung

$\verb|mcopper|: Monthly copper| prices. Copper, grade A, electrolytic wire bars/cathodes, LME, cash (pounds/ton)$

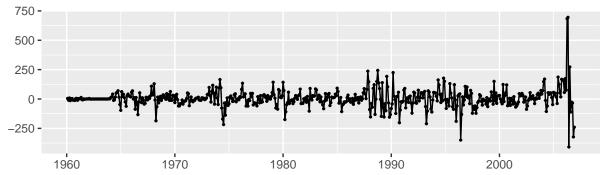
```
### plot raw data series
autoplot(mcopper) +
   ggtitle(paste("mcopper (untransformed)")) +
   theme(plot.title = element_text(hjust = 0.5))+
   geom_line(color="red")
```

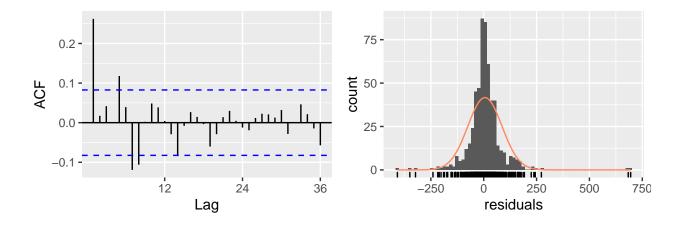
mcopper (untransformed)



mcopper.ljung <- checkresiduals(naive(mcopper))</pre>

Residuals from Naive method



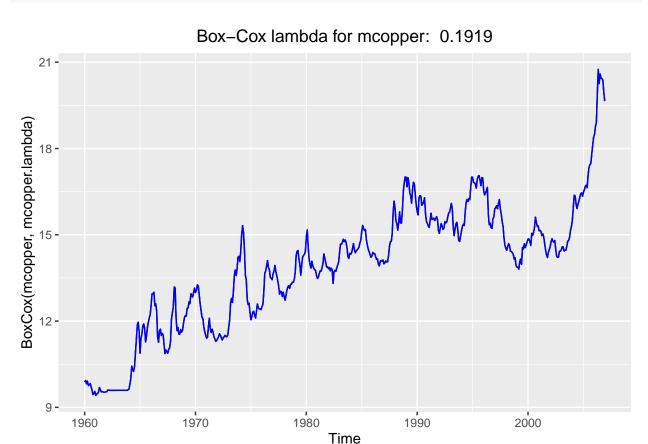


```
##
## Ljung-Box test
##
## data: Residuals from Naive method
## Q* = 74.063, df = 24, p-value = 0.0000005216
##
## Model df: 0. Total lags used: 24
```

[1] "Because the p-value on the Ljung-Box test is small, \n we'll try Box-Cox transform to

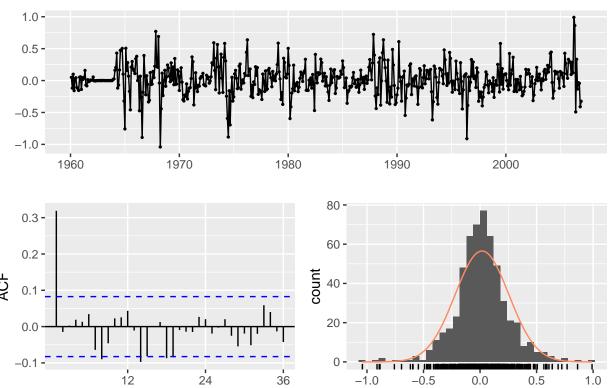
```
### Box-Cox transform
mcopper.lambda <- BoxCox.lambda(mcopper)
### Plot transformed series
#print(paste("Box-Cox lambda for mcopper: ", round(mcopper.lambda,3)))
autoplot(BoxCox(mcopper, mcopper.lambda)) +
    ggtitle(paste("Box-Cox lambda for mcopper: ", round(mcopper.lambda,4))) +</pre>
```

```
theme(plot.title = element_text(hjust = 0.5))+
geom_line(color="blue")
```



mcopper.xform.ljung <- checkresiduals(naive(BoxCox(mcopper, mcopper.lambda)))</pre>

Residuals from Naive method



−**1**.0

0.5

1.0

0.0

residuals

```
##
    Ljung-Box test
##
##
## data: Residuals from Naive method
## Q* = 87.597, df = 24, p-value = 0.000000003588
##
## Model df: 0. Total lags used: 24
```

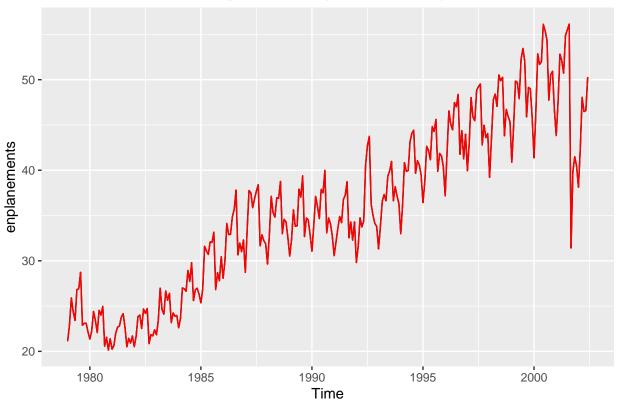
Lag

#mcopper.xform.ljung

enplanements: Monthly US domestic enplanements (millions): 1996-2000

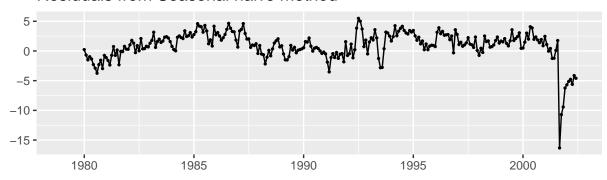
```
### plot raw data series
autoplot(enplanements) +
   ggtitle(paste("enplanements (untransformed)")) +
   theme(plot.title = element_text(hjust = 0.5))+
   geom_line(color="red")
```

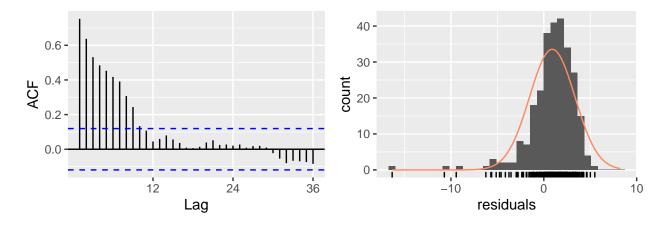
enplanements (untransformed)



enplanements.ljung <- checkresiduals(snaive(enplanements))</pre>

Residuals from Seasonal naive method





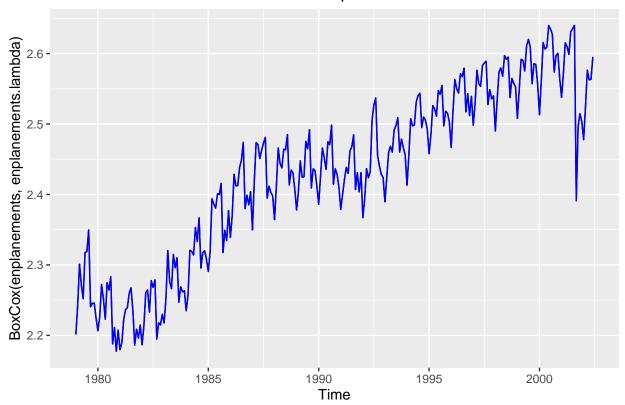
```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 614.48, df = 24, p-value < 0.00000000000000022
##
## Model df: 0. Total lags used: 24</pre>
```

[1] "Because the p-value on the Ljung-Box test is small, \n we'll try Box-Cox transform to

```
### Box-Cox transform
enplanements.lambda <- BoxCox.lambda(enplanements)
### Plot transformed series
#print(paste("Box-Cox lambda for enplanements: ", round(enplanements.lambda,3)))
autoplot(BoxCox(enplanements, enplanements.lambda)) +
    ggtitle(paste("Box-Cox lambda for enplanements: ", round(enplanements.lambda,4))) +</pre>
```

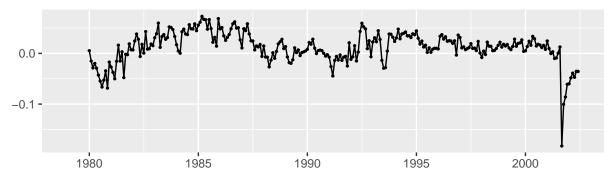
```
theme(plot.title = element_text(hjust = 0.5))+
geom_line(color="blue")
```

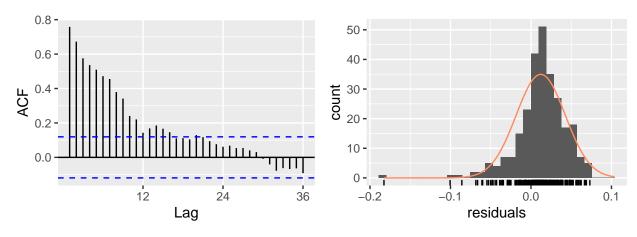
Box-Cox lambda for enplanements: -0.2269



enplanements.xform.ljung <- checkresiduals(snaive(BoxCox(enplanements, enplanements.lambda)))</pre>

Residuals from Seasonal naive method





```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 809.1, df = 24, p-value < 0.0000000000000000022
##
## Model df: 0. Total lags used: 24</pre>
```

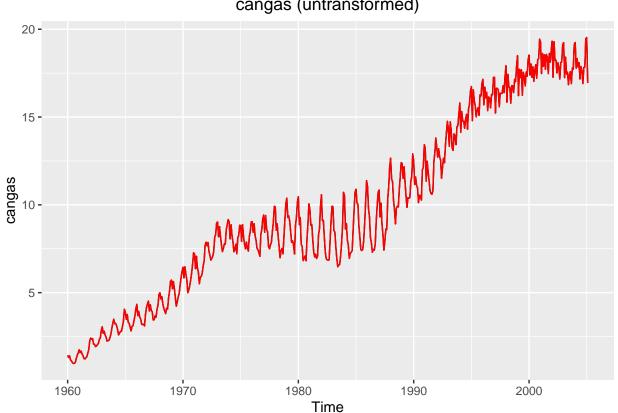
#enplanements.xform.ljung

3.2 Why is a Box-Cox transformation unhelpful for the cangas data?

cangas: Monthly Canadian gas production, billions of cubic metres, January 1960 - February 2005

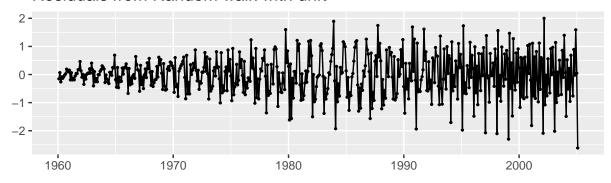
```
### plot raw data series
autoplot(cangas) +
  ggtitle(paste("cangas (untransformed)")) +
  theme(plot.title = element_text(hjust = 0.5))+
 geom_line(color="red")
```

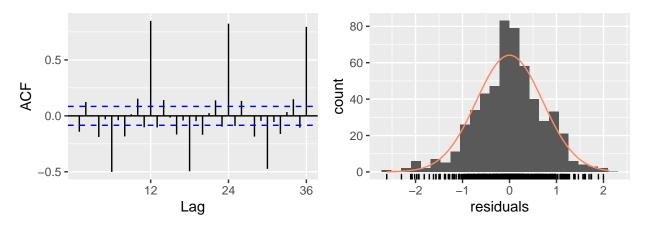
cangas (untransformed)



cangas.ljung <- checkresiduals(rwf(cangas,h=2*frequency(cangas),drift=T))</pre>

Residuals from Random walk with drift



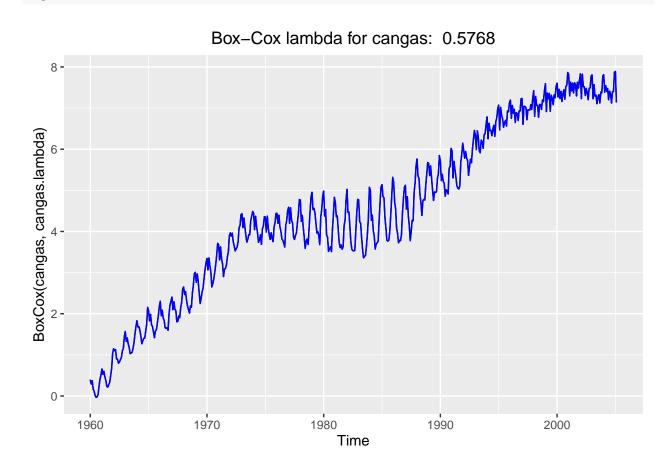


```
##
## Ljung-Box test
##
## data: Residuals from Random walk with drift
## Q* = 1207.3, df = 23, p-value < 0.00000000000000022
##
## Model df: 1. Total lags used: 24</pre>
```

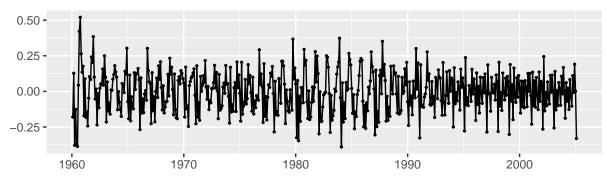
[1] "Because the p-value on the Ljung-Box test is small, \n we'll try Box-Cox transform to

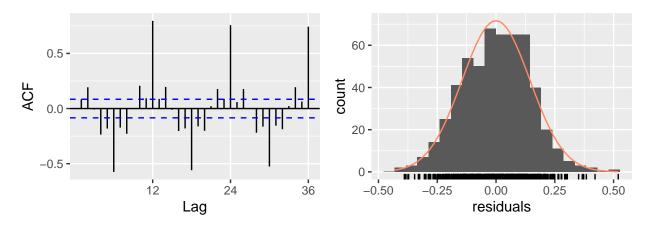
```
### Box-Cox transform
cangas.lambda <- BoxCox.lambda(cangas)
### Plot transformed series
#print(paste("Box-Cox lambda for cangas: ", round(cangas.lambda,3)))
autoplot(BoxCox(cangas, cangas.lambda)) +
    ggtitle(paste("Box-Cox lambda for cangas: ", round(cangas.lambda,4))) +</pre>
```

```
theme(plot.title = element_text(hjust = 0.5))+
geom_line(color="blue")
```









```
##
## Ljung-Box test
##
## data: Residuals from Random walk with drift
## Q* = 1307.8, df = 23, p-value < 0.00000000000000022
##
## Model df: 1. Total lags used: 24</pre>
```

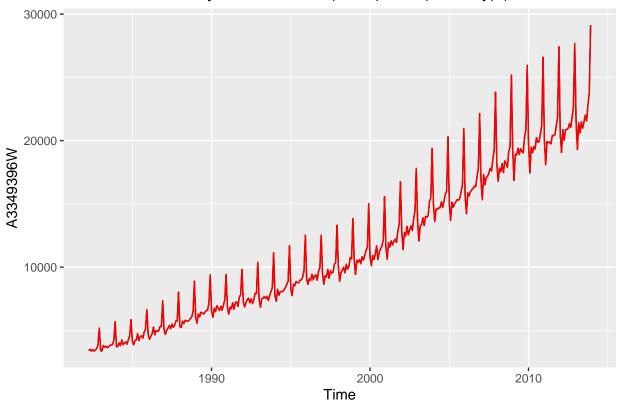
#cangas.xform.ljung

The raw data series for cangas exhibits much higher variance during the middle years (late 1970s through early 1990s) and lower variance in the early and later years. The Box-Cox transformation is unable to stabilize this pattern.

3.3. What Box-Cox transformation would you select for your retail data (from Exercise 3 in Section 2.10)?

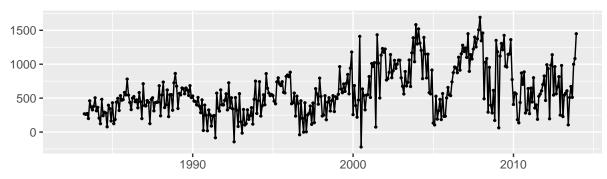
```
#### You can read the data into R with the following script:
#### readxl does not read straight from URL without local download
####retaildata <- readxl::read_excel("https://otexts.com/fpp2/extrafiles/retail.xlsx", skip=1)
retaildata <- readxl::read_excel("retail.xlsx", skip=1)</pre>
#### The second argument (`skip=1`) is required because the Excel sheet has two header rows.
##myts <- ts(retaildata[,"A3349873A"],
## frequency=12, start=c(1982,4))
#### Select one of the time series as follows
#### (but replace the column name with your own chosen column):
mycode <- "A3349396W"
mytitle <- "Monthly Turnover; Total(State); Total(Industry)"</pre>
mymain <- paste(mycode,mytitle)</pre>
myts <- ts(retaildata[,"A3349396W"],</pre>
 frequency=12, start=c(1982,4))
### plot raw data series
autoplot(myts) +
  ggtitle(paste(mymain, "(untransformed)")) +
  ylab(mycode)+
  theme(plot.title = element_text(hjust = 0.5))+
  geom_line(color="red")
```

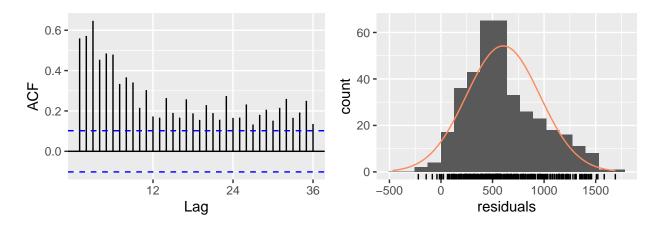
A3349396W Monthly Turnover; Total (State); Total (Industry) (untransformed)



myts.ljung <- checkresiduals(snaive(myts))</pre>

Residuals from Seasonal naive method





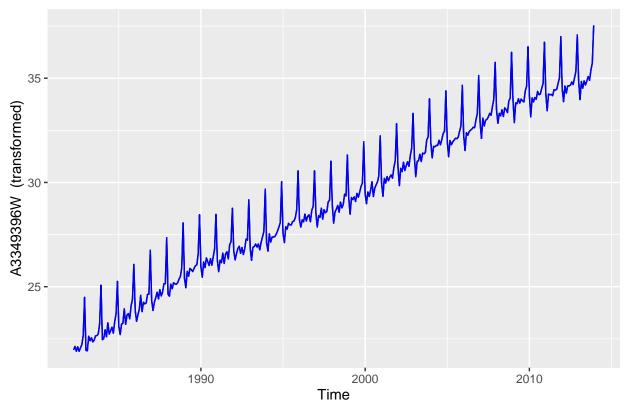
```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 1045.2, df = 24, p-value < 0.000000000000000022
##
## Model df: 0. Total lags used: 24</pre>
```

[1] "Because the p-value on the Ljung-Box test is small, \n we'll try Box-Cox transform to

```
### Box-Cox transform
myts.lambda <- BoxCox.lambda(myts)
### Plot transformed series
#print(paste("Box-Cox lambda for myts: ", round(myts.lambda,3)))
autoplot(BoxCox(myts, myts.lambda)) +
    ggtitle(paste("Box-Cox lambda for", mycode, ": ", round(myts.lambda,4))) +</pre>
```

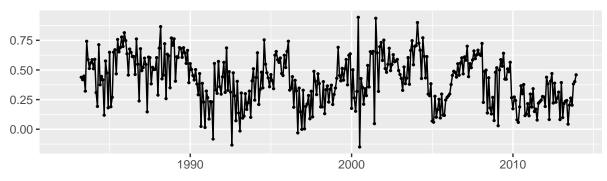
```
ylab(paste(mycode," (transformed)"))+
theme(plot.title = element_text(hjust = 0.5))+
geom_line(color="blue")
```

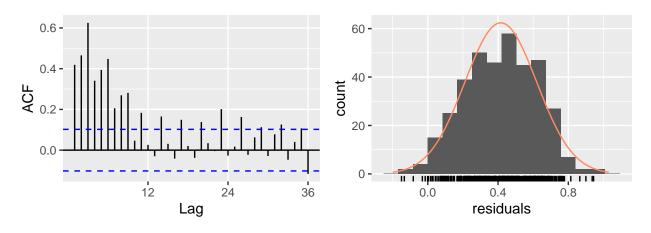
Box-Cox lambda for A3349396W: 0.2142



myts.xform.ljung <- checkresiduals(snaive(BoxCox(myts, myts.lambda)))</pre>

Residuals from Seasonal naive method





```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 602.81, df = 24, p-value < 0.000000000000000022
##
## Model df: 0. Total lags used: 24</pre>
```

#myts.xform.ljung

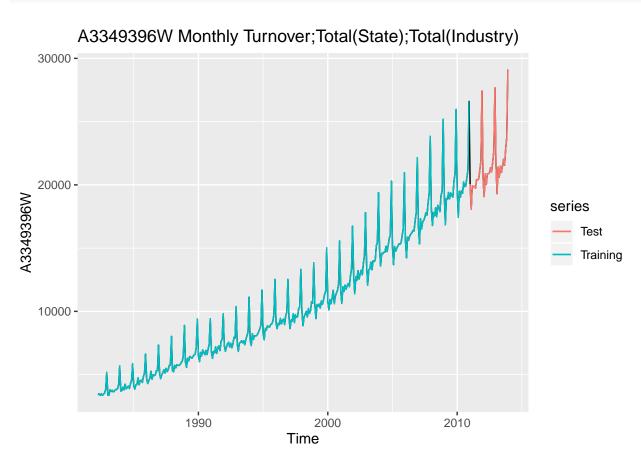
The Box-Cox transformation selected for this data series is $\lambda=0.2142$.

- 3.8 For your retail time series (from Exercise 3 in Section 2.10):
- a) Split the data into two parts using

```
myts.train <- window(myts, end=c(2010,12))
myts.test <- window(myts, start=2011)</pre>
```

b) Check that your data have been split appropriately by producing the following plot.

```
autoplot(myts) +
  autolayer(myts.train, series="Training") +
  autolayer(myts.test, series="Test") +
  ggtitle(mymain)+
  ylab(mycode)
```



c) Calculate forecasts using snaive applied to myts.train.

Note: To get 36 months of forecast (3 years) we have to specify h=36

```
fc <- snaive(myts.train,h=length(myts.test))
fc</pre>
```

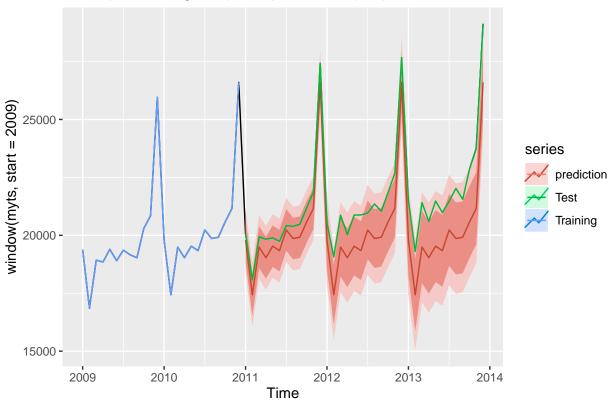
If we don't specify a value for h then we will get the default, which is only 2 years (24 months)

```
Point Forecast
                              Lo 80
                                       Hi 80
                                                 Lo 95
                                                          Hi 95
## Jan 2011
                   19792.0 18895.89 20688.11 18421.52 21162.48
## Feb 2011
                   17431.5 16535.39 18327.61 16061.02 18801.98
## Mar 2011
                   19490.3 18594.19 20386.41 18119.82 20860.78
## Apr 2011
                   19032.0 18135.89 19928.11 17661.52 20402.48
## May 2011
                   19533.6 18637.49 20429.71 18163.12 20904.08
## Jun 2011
                   19339.1 18442.99 20235.21 17968.62 20709.58
## Jul 2011
                   20231.6 19335.49 21127.71 18861.12 21602.08
## Aug 2011
                   19860.8 18964.69 20756.91 18490.32 21231.28
## Sep 2011
                   19916.3 19020.19 20812.41 18545.82 21286.78
## Oct 2011
                   20575.4 19679.29 21471.51 19204.92 21945.88
## Nov 2011
                   21163.7 20267.59 22059.81 19793.22 22534.18
## Dec 2011
                   26599.2 25703.09 27495.31 25228.72 27969.68
## Jan 2012
                   19792.0 18524.71 21059.29 17853.85 21730.15
## Feb 2012
                   17431.5 16164.21 18698.79 15493.35 19369.65
## Mar 2012
                   19490.3 18223.01 20757.59 17552.15 21428.45
                   19032.0 17764.71 20299.29 17093.85 20970.15
## Apr 2012
## May 2012
                   19533.6 18266.31 20800.89 17595.45 21471.75
## Jun 2012
                   19339.1 18071.81 20606.39 17400.95 21277.25
## Jul 2012
                   20231.6 18964.31 21498.89 18293.45 22169.75
## Aug 2012
                   19860.8 18593.51 21128.09 17922.65 21798.95
## Sep 2012
                   19916.3 18649.01 21183.59 17978.15 21854.45
## Oct 2012
                   20575.4 19308.11 21842.69 18637.25 22513.55
## Nov 2012
                   21163.7 19896.41 22430.99 19225.55 23101.85
## Dec 2012
                   26599.2 25331.91 27866.49 24661.05 28537.35
## Jan 2013
                   19792.0 18239.90 21344.10 17418.26 22165.74
## Feb 2013
                   17431.5 15879.40 18983.60 15057.76 19805.24
## Mar 2013
                   19490.3 17938.20 21042.40 17116.56 21864.04
## Apr 2013
                   19032.0 17479.90 20584.10 16658.26 21405.74
## May 2013
                   19533.6 17981.50 21085.70 17159.86 21907.34
## Jun 2013
                   19339.1 17787.00 20891.20 16965.36 21712.84
## Jul 2013
                   20231.6 18679.50 21783.70 17857.86 22605.34
## Aug 2013
                   19860.8 18308.70 21412.90 17487.06 22234.54
## Sep 2013
                   19916.3 18364.20 21468.40 17542.56 22290.04
## Oct 2013
                   20575.4 19023.30 22127.50 18201.66 22949.14
## Nov 2013
                   21163.7 19611.60 22715.80 18789.96 23537.44
## Dec 2013
                   26599.2 25047.10 28151.30 24225.46 28972.94
```

d) Compare the accuracy of your forecasts against the actual values stored in myts.test.

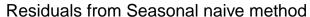
```
accuracy(fc,myts.test)
##
                              RMSE
                                        MAE
                                                 MPE
                                                         MAPE
                                                                   MASE
                                                                             ACF1 Theil's U
                       ME
                                   601.506 5.961516 5.997664 1.000000 0.5972618
## Training set
                598.4838
                           699.236
                                                                                         NA
## Test set
                1230.1556 1389.337 1230.156 5.668187 5.668187 2.045126 0.7093345 0.6485265
autoplot(window(myts,start=2009)) +
  ggtitle(paste("Actual (blue and green) and prediction (red) for", mycode))+
  theme(plot.title = element_text(hjust = 0.5))+
  autolayer(window(myts.train,start=2009), series="Training") +
  autolayer(fc, series="prediction")+
  autolayer(myts.test, series="Test", )
```

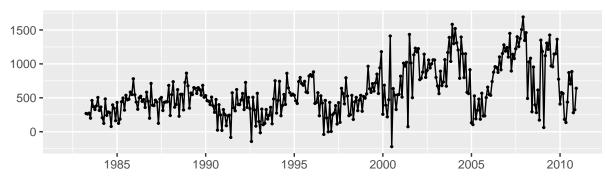
Actual (blue and green) and prediction (red) for A3349396W

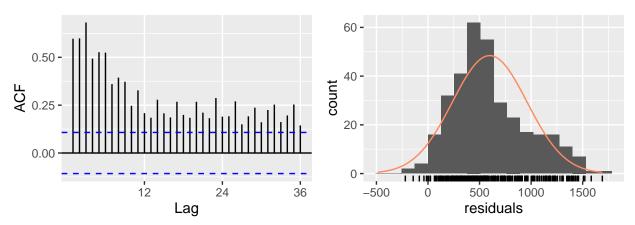


e) Check the residuals.

checkresiduals(fc)







```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 1101, df = 24, p-value < 0.0000000000000000022
##
## Model df: 0. Total lags used: 24</pre>
```

Do the residuals appear to be uncorrelated and normally distributed? No, the residuals exhibit strong autocorrelation across all lags. Additionally the histogram shows much more density to the left of the mode, with a right tail. The residuals are clearly biased as they do not account for the year-over-year upward trend observed in the actual data; a seasonal trend model would be more appropriate.

f) How sensitive are the accuracy measures to the training/test split?

Below I take the dataset and rerun the naive model a dozen times, each time moving one additional year's worth of data between training and test. We start with the year 2000 being the cut-point between training and test, and advance one year at a time until reaching 2012.

The summary of the sensitivity is as follows:

As more data is moved into the TRAINING set, and less data is in the TEST set:

- The accuracy of all TEST metrics improves:
 - i.e., the **TEST** MAE, RMSE, ME, MAPE, MASE, and MPE all become **SMALLER**.
- The change in accuracy of the TRAINING** metrics is not uniform:
 - The accuracy of the **TRAINING** MAE, RMSE, and ME actually **WORSEN** (i.e., become **LARGER**), while
 - the **TRAINING** MAPE and MPE initially **WORSEN**, but then eventually **IMPROVE**.

The results are displayed below.

```
firstyear = TRUE
## Loop through 13 years
for (year in 2000:2012) {
  myts.train <- window(myts, end=c(year,12))</pre>
  myts.test <- window(myts, start=year+1)</pre>
  fc <- snaive(myts.train,h=length(myts.test))</pre>
  #print(length(fc$mean))
  #print(paste("YEAR: ", year, "TRAINING SIZE: ", length(myts.train), "TEST SIZE: ",length(myts.test) ))
  ac=accuracy(fc,myts.test)
  if(firstyear == TRUE) {
    # split the "train" and "test" metrics out into two separate matrices for train and test accuracy:
    trainac = c(YEAR=year, TRAINSIZE=length(myts.train), ac[1,])
    testac = c(YEAR=year, TESTSIZE=length(myts.test), ac[2,])
    firstyear = FALSE
  else {
    # append the results from this year onto the existing matrices for train accuracy and test accuracy:
    trainac = rbind(trainac, c(YEAR=year,TRAINSIZE=length(myts.train),ac[1,]))
    testac = rbind(testac, c(YEAR=year,TESTSIZE=length(myts.test), ac[2,]))
}
```

```
# display the results of the Train Accuracy matrix
print(trainac)
```

Accuracy metrics for TRAIN data set

```
##
           YEAR TRAINSIZE
                                ME
                                       RMSE
                                                 MAE
                                                          MPE
                                                                  MAPE MASE
                                                                                  ACF1 Theil's U
## trainac 2000
                      225 441.8272 496.1132 446.5521 6.226271 6.282784
                                                                          1 0.2244231
                                                                                              NA
##
           2001
                      237 466.6796 532.8469 471.1524 6.282127 6.335626
                                                                          1 0.2828268
                                                                                              NA
##
           2002
                      249 492.0793 563.9284 496.3257 6.332516 6.383306
                                                                          1 0.3985305
                                                                                              NA
                                                                          1 0.4452951
##
           2003
                      261 513.5542 591.2021 517.5960 6.338633 6.386976
                                                                                              NA
##
           2004
                      273 538.4889 623.7055 542.3448 6.370047 6.416167
                                                                          1 0.5321618
                                                                                              NA
           2005
                      285 529.9436 615.2940 533.6300 6.184376 6.228469
##
                                                                          1 0.5231794
                                                                                              NA
##
           2006
                      297 546.6414 633.1954 550.1726 6.157042 6.199278
                                                                          1 0.5515157
                                                                                              NA
           2007
##
                      309 576.2492 672.7710 579.6377 6.196449 6.236978
                                                                          1 0.6144665
                                                                                              NA
##
           2008
                      321 584.5184 683.3828 587.7754 6.120005 6.158961
                                                                          1 0.5946147
                                                                                              NA
##
           2009
                      333 602.1380 704.0654 605.2732 6.091628 6.129127
                                                                          1 0.6024399
                                                                                              NA
                      345 598.4838 699.2360 601.5060 5.961516 5.997664
##
           2010
                                                                          1 0.5972618
                                                                                              NA
##
           2011
                      357 596.0075 694.9102 598.9246 5.842082 5.876972
                                                                                              NA
                                                                          1 0.5918599
           2012
                      369 599.8387 697.5348 602.6577 5.759032 5.792750
##
                                                                          1 0.5727110
                                                                                              NA
```

```
# make it into a data frame, for easier plotting
traindf <- as.data.frame(trainac)
traindf$YEAR <- as.integer(traindf$YEAR)
traindf$DATE <- ISOdate(traindf$YEAR,01,01)

colors <- c("RMSE" = "blue", "MAE" = "red", "ME" = "green")

ggplot(traindf, aes(x = DATE)) +
    geom_line(aes(y = MAE, color = "MAE"), linetype="dotted", size = 1.5) +
    geom_line(aes(y = RMSE, color = "RMSE"), size = 1.5) +
    geom_line(aes(y = ME, color = "ME"), linetype="dashed", size = 1.5) +
    labs(x = "Year of Train/Test Split",
        y = "Metric",
        color = "Legend") +
    scale_color_manual(values = colors)+
    xlim(ISOdate(2000,01,01),ISOdate(2012,01,01))+
    ggtitle("Accuracy Metrics for TRAIN data set based upon date of Train/Test split")</pre>
```

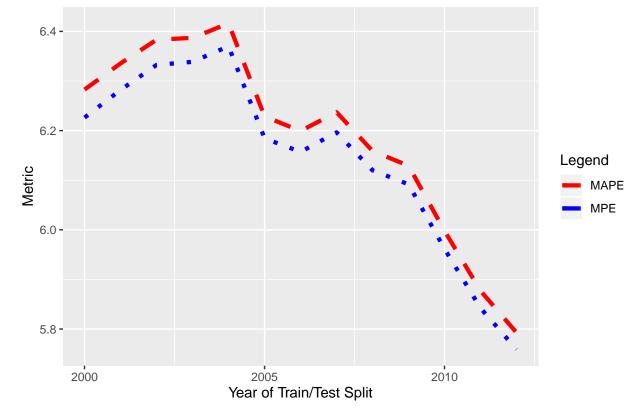
Accuracy Metrics for TRAIN data set based upon date of Train/Test split



```
colors <- c("MPE" = "blue", "MAPE" = "red", "MASE" = "green")

ggplot(traindf, aes(x = DATE)) +
    geom_line(aes(y = MPE, color = "MPE"), linetype="dotted", size = 1.5) +
    geom_line(aes(y = MAPE, color = "MAPE"), linetype="dashed", size = 1.5) +
    labs(x = "Year of Train/Test Split",
        y = "Metric",
        color = "Legend") +
    scale_color_manual(values = colors)+
    xlim(ISOdate(2000,01,01),ISOdate(2012,01,01))+
    ggtitle("Accuracy Metrics for TRAIN data set based upon date of Train/Test split")</pre>
```

Accuracy Metrics for TRAIN data set based upon date of Train/Test split



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##

2012

Accuracy metrics for TEST data set

print(testac)

```
YEAR TESTSIZE
                                      RMSE
                                                                             MASE
##
                             ME
                                                MAE
                                                          MPE
                                                                   MAPE
                                                                                       ACF1 Theil's U
## testac 2000
                    156 6112.876 6892.8262 6112.876 32.553804 32.553804 13.689053 0.9337717 3.2207222
##
          2001
                    144 5638.823 6330.5128 5638.823 29.528101 29.528101 11.968150 0.9486687 2.9191664
##
          2002
                    132 5095.089 5725.8973 5095.089 26.174141 26.174141 10.265614 0.9364892 2.6141260
##
          2003
                    120 4573.146 5134.2088 4573.146 23.164552 23.164552 8.835358 0.9438856 2.3266503
##
          2004
                    108 3908.069 4457.8267 3908.069 19.277010 19.277010 7.205876 0.9222842 2.0008593
##
          2005
                     96 4009.484 4397.8005 4009.484 19.694820 19.694820 7.513603 0.9174346 1.9795269
##
          2006
                     84 3523.392 3809.2684 3523.392 17.121308 17.121308 6.404157 0.8926470 1.6967257
##
          2007
                     72 2617.951 2875.0868 2617.951 12.543746 12.543746 4.516530 0.8693843 1.2654264
##
         2008
                     60 2194.522 2387.0439 2194.522 10.388966 10.388966 3.733606 0.8016731 1.0665422
##
          2009
                     48 1423.350 1629.8337 1423.350 6.629138 6.629138 2.351583 0.8135086 0.7346592
##
          2010
                     36 1230.156 1389.3374 1230.156 5.668187 5.668187 2.045126 0.7093345 0.6485265
                     24 1054.296 1150.4211 1054.296 4.830782 4.830782 1.760315 0.2867600 0.5760630
##
          2011
```

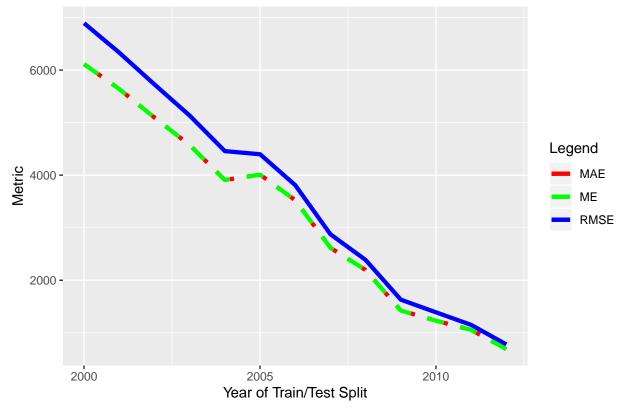
```
testdf <- as.data.frame(testac)
testdf$YEAR <- as.integer(testdf$YEAR)
testdf$DATE <- ISOdate(testdf$YEAR,01,01)

colors <- c("RMSE" = "blue", "MAE" = "red", "ME" = "green")

ggplot(testdf, aes(x = DATE)) +
    geom_line(aes(y = MAE, color = "MAE"), linetype="dotted", size = 1.5) +
    geom_line(aes(y = RMSE, color = "RMSE"), size = 1.5) +
    geom_line(aes(y = RMSE, color = "RMSE"), size = 1.5) +
    labs(x = "Year of Train/Test Split",
        y = "Metric",
        color = "Legend") +
    scale_color_manual(values = colors)+
    xlim(ISOdate(2000,01,01),ISOdate(2012,01,01))+
    ggtitle("Accuracy Metrics for TEST data set based upon date of Train/Test split")</pre>
```

12 688.625 777.9451 688.625 3.008222 3.008222 1.142647 0.3078987 0.3891341

Accuracy Metrics for TEST data set based upon date of Train/Test split

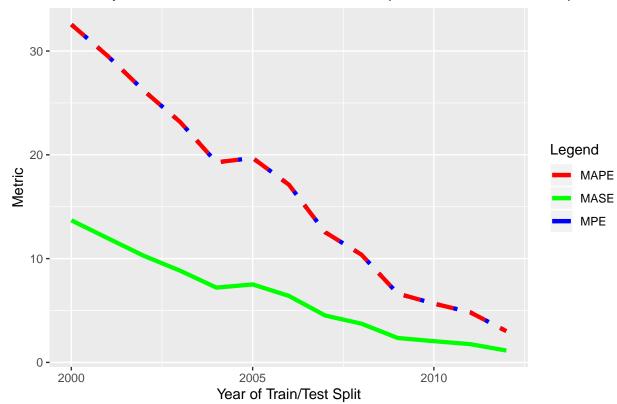


```
colors <- c("MPE" = "blue", "MAPE" = "red", "MASE" = "green")

ggplot(testdf, aes(x = DATE)) +
    geom_line(aes(y = MPE, color = "MPE"), linetype="dotted", size = 1.5) +
    geom_line(aes(y = MASE, color = "MASE"), size = 1.5) +
    geom_line(aes(y = MAPE, color = "MAPE"), linetype="dashed", size = 1.5) +
    labs(x = "Year of Train/Test Split",
        y = "Metric",
        color = "Legend") +
    scale_color_manual(values = colors)+
    xlim(ISOdate(2000,01,01),ISOdate(2012,01,01))+</pre>
```

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Accuracy Metrics for TEST data set based upon date of Train/Test split



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