

# W271 Lab 3

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```
# add packages
library(forecast)
library(knitr)
library(stats)
library(tseries)
library(xts)
# prevent source code from running off the page
opts_chunk$set(tidy.opts=list(width.cutoff=70), tidy=TRUE)
# remove all objects from current workspace
rm(list = ls())
# set seed number to reproduce results
set.seed(1)
# load data
raw.sales <- read.csv('./data/ECOMPCTNSA.csv', header=TRUE, sep=',')
```

## Question 1: Forecasting using a SARIMA model

Since the emergence of the internet, more and more people are shopping at online retailers than brick-and-mortar stores. E-commerce is on the rise, and we would like to see what percentage of total retail sales e-commerce is accounted for in the fourth quarter of 2017. With data from the US Census Bureau ranging from 1999 to 2016, we were able to estimate it to be 11.44% using the seasonal autoregressive integrated moving average model (or SARIMA for short). While the number does not seem substantial compare to the perceived value of e-commerce, we have to remember that retail sales include motor vehicles, gas stations, and grocery stores where e-commerce has yet to play a major role in the field.

The SARIMA model that we use for the projected forecast is  $ARIMA(1, 2, 1)(1, 2, 1)_4$ .

### Exploration Data Analysis

The first step once we obtained the dataset was to examine its structure.

```
# convert raw data into a time-series object
sales <- ts(raw.sales$ECOMPCTNSA, start = c(1999, 4), frequency = 4)
# hold out test data for verification in forecast
sales.train <- ts(sales[time(sales) < 2015], start = c(1999, 4), frequency = 4) # 1999-2014
sales.test <- ts(sales[time(sales) >= 2015], start = c(2015, 1), frequency = 4) # 2015-2016
# examine the structure
kable(summary(raw.sales))
```

DATE	ECOMPCTNSA
1999-10-01: 1	Min. :0.700
2000-01-01: 1	1st Qu.:2.000

DATE	ECOMPCTNSA
2000-04-01: 1	Median :3.600
2000-07-01: 1	Mean :3.835
2000-10-01: 1	3rd Qu.:5.300
2001-01-01: 1	Max. :9.500
(Other) :63	NA

```
head(sales)
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 1999              0.7
## 2000  0.8  0.8  0.9  1.1
## 2001  1.1
```

```
tail(sales)
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 2015              6.8  8.7
## 2016  7.7  7.5  7.7  9.5
```

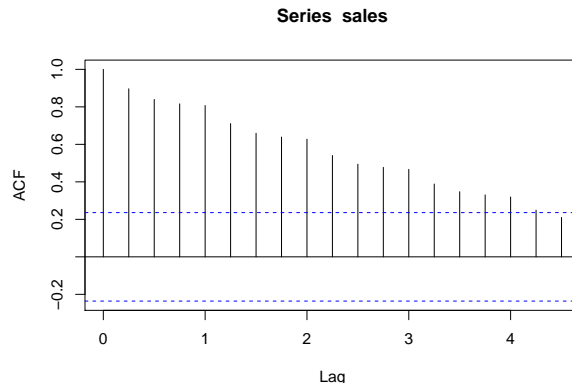
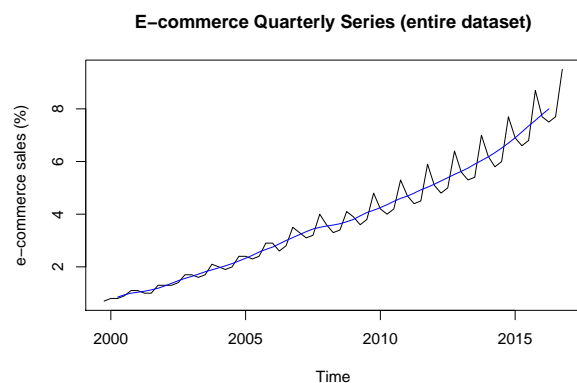
We were able to determine that there was no missing value among the 69 observations with sales appearing to increase overtime from 0.7% in the 4th quarter of 1999 to 9.5% in the 4th quarter of 2016. To confirm, we plot the time series as well as its associating MA(4) model. If the data expressed seasonality every quarter, the MA(4) model smooths out the variances and acts as an annual trend with the seasonal effects within each quarter removed.

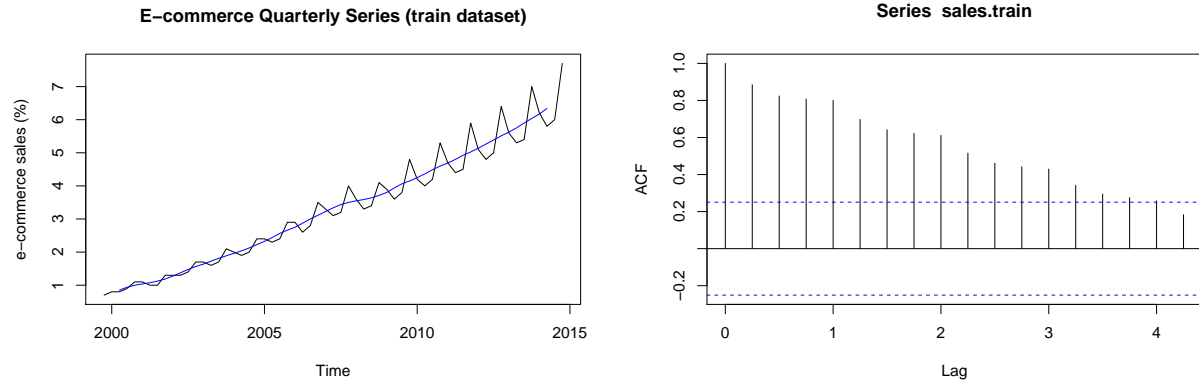
```
# using the entire dataset
```

```
plot(sales, ylab = "e-commerce sales (%)", main = "E-commerce Quarterly Series (entire dataset)",
lines(ma(sales, order = 4, centre = T), col = "blue")
acf(sales)
```

```
# using the train dataset
```

```
plot(sales.train, ylab = "e-commerce sales (%)", main = "E-commerce Quarterly Series (train data)",
lines(ma(sales.train, order = 4, centre = T), col = "blue")
acf(sales.train)
```





Given the upward trend and increasing variance, the series is non-stationary with quarterly seasonality. The autocorrelation function further substantiates the series's non-stationary because of its slow decay and  $r_1$ s that are large and positive ( $r_1$  indicates how successive values of  $y$  relate to each other). For this reason, we will perform two operations. One, we will difference the series to stabilize the mean. And two, we will apply a Box-Cox transformation (logarithm and power transformation) to stabilize the variance. We verify if differencing was necessary by running the unit root test.

```
# unit root test
cbind(adf.test(sales.train, alternative = "stationary")$p.value, kpss.test(sales.train)$p.value,
      nsdiffs(sales.train))
```

```
##      [,1] [,2] [,3]
## [1,] 0.99 0.01  1
```

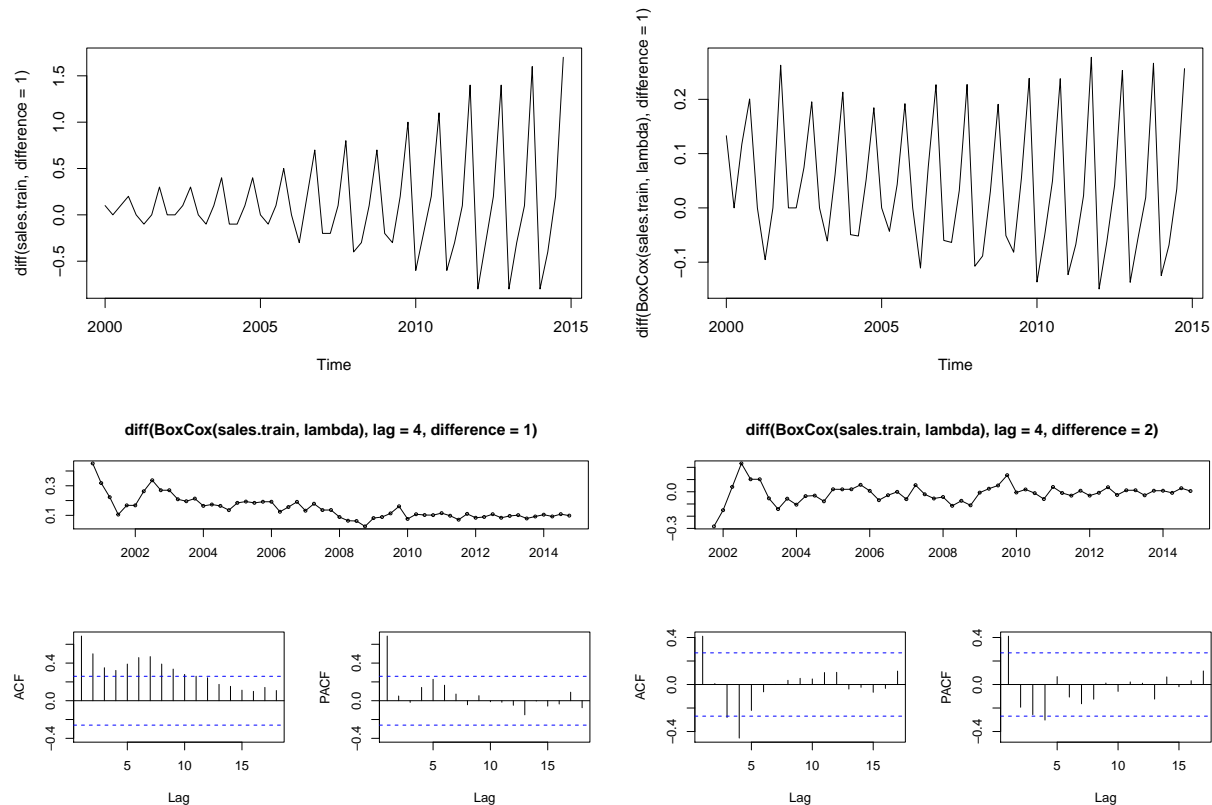
Large p-value in the Augmented Dickey-Fuller (ADF) test and small p-value in the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test confirm our intuition to difference the time series. Although the seasonal unit test suggests to difference the data once, we decide to difference it a second time in order to make the series stationary (as implied by the two unit root tests we run before: ADF and KPSS). We apply log and power transformation to the difference using the Box-Cox transformation by first finding the best lambda value that will give the optimal uniformity in the seasonal variation before administering the said transformation.

```
# find the best lambda for Box-Cox transformation
lambda <- BoxCox.lambda(sales.train) # lambda = 0.01467236
# first-order differenced series plot
plot(diff(sales.train, difference = 1))
# first-order differenced BoxCox-transformed series plot
plot(diff(BoxCox(sales.train, lambda), difference = 1))
# first-order differenced BoxCox-transformed series
tsdisplay(diff(BoxCox(sales.train, lambda), lag = 4, difference = 1))
# second-order differenced BoxCox-transformed series
tsdisplay(diff(BoxCox(sales.train, lambda), lag = 4, difference = 2))
# unit root test on first-order differenced log-transformed series
cbind(adf.test(diff(BoxCox(sales.train, lambda), lag = 4, difference = 1),
               alternative = "stationary")$p.value, kpss.test(diff(BoxCox(sales.train,
               lambda), lag = 4, difference = 1))$p.value)
```

```
##          [,1] [,2]
## [1,] 0.0109321 0.01
```

```
# unit root test on first-order differenced log-transformed series
cbind(adf.test(diff(BoxCox(sales.train, lambda), lag = 4, difference = 2),
  alternative = "stationary")$p.value, kpss.test(diff(BoxCox(sales.train,
  lambda), lag = 4, difference = 2))$p.value)
```

```
##          [,1] [,2]
## [1,] 0.01 0.1
```



## Modeling

Looking at the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the second order differenced, we estimate the best-fitting model to be  $ARIMA(1, 2, 1)(1, 2, 1)_4$ .

- In the non-seasonal lags, the significant spike at lag 1 in the PACF suggests a possible non-seasonal  $AR(1)$  term.
- In the seasonal lags, the significant spike at lag 4 in the PACF suggests a possible seasonal  $AR(1)$  term.
- In the non-seasonal lags, the significant spike at lag 1 in the ACF suggests a possible non-seasonal  $MA(1)$  term.
- In the seasonal lags, the significant spike at lag 4 in the ACF suggests a possible seasonal  $MA(1)$  term.

```
(base.m <- Arima(BoxCox(sales.train, lambda), order = c(1, 2, 1), seasonal = list(order = c(1, 2, 1), 4)))
```

```
## Series: BoxCox(sales.train, lambda)
## ARIMA(1,2,1)(1,2,1)[4]
##
## Coefficients:
##          ar1          ma1          sar1          sma1
##      -0.1209   -0.9920   -0.6971   -0.9902
## s.e.    0.1595    0.1265    0.1240    0.1397
##
## sigma^2 estimated as 0.001313: log likelihood=84.45
## AIC=-158.91   AICc=-157.57   BIC=-149.25
```

By iterating through multiple parameters, we can find the second best-fitting model under the AICc criterion:  $\text{ARIMA}(0, 2, 1)(0, 2, 2)_4$ .

```
best.manual.m <- base.m
for (P in 0:2) for (Q in 0:2) for (p in 0:2) for (q in 0:2) {
  m <- Arima(BoxCox(sales.train, lambda), order = c(P, 2, Q), seasonal = list(order = c(p, 2, q)))
  if (m$aicc < best.manual.m$aicc)
    best.manual.m <- m
}
best.manual.m
```

```
## Series: BoxCox(sales.train, lambda)
## ARIMA(0,2,1)(0,2,2)[4]
##
## Coefficients:
##          ma1          sma1          sma2
##      -0.9897   -1.9016    0.9549
## s.e.    0.1436    0.2819    0.2768
##
## sigma^2 estimated as 0.001005: log likelihood=86.06
## AIC=-164.12   AICc=-163.25   BIC=-156.39
```

We compare our generated best-fitting model to the one generated by the `auto.arima` function and found it to be a first-order differenced series:  $\text{ARIMA}(0, 1, 0)(0, 1, 2)_4$ .

```
(best.auto.m <- auto.arima(BoxCox(sales.train, lambda), ic = "aicc", stepwise = FALSE, approximation = FALSE))
```

```
## Series: BoxCox(sales.train, lambda)
## ARIMA(0,1,0)(0,1,2)[4]
##
## Coefficients:
##          sma1          sma2
##      -0.7670    0.4052
## s.e.    0.1545    0.1342
```

```
##
## sigma^2 estimated as 0.001301: log likelihood=106.17
## AIC=-206.35 AICc=-205.88 BIC=-200.27
```

Although we know that first-order differencing does not pass the unit root test KPSS, we will use the model derived from the `auto.arima` function as a comparison model. The three models that we will take a look at moving forward are the one we derived manually (ARIMA(1, 2, 1)(1, 2, 1)<sub>4</sub>), the one we automated manually (ARIMA(0, 2, 1)(0, 2, 2)<sub>4</sub>) and the one we generated from the `auto.arima` function (ARIMA(0, 1, 0)(0, 1, 2)<sub>4</sub>).

## Validating the models

Before we can forecast what percentage of total retail sales e-commerce sales will be in the future, we first need to validate that the residuals from the three models result in the following properties:

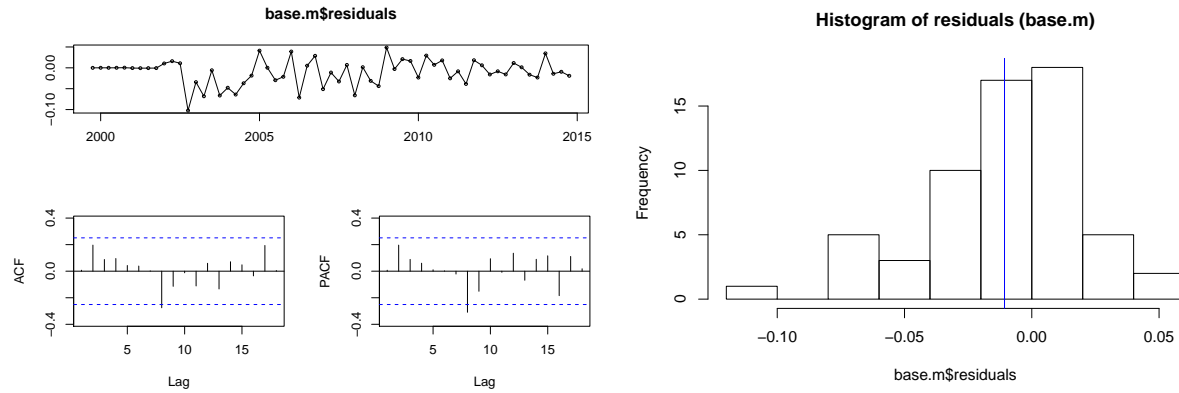
- uncorrelated, meaning there is no information left in the residuals that can be used in computing the forecast
- zero mean
- constant variance
- normally distributed

```
# base.m autocorrelations -> to test uncorrelated and view variance
tsdisplay(base.m$residuals)
# group of autocorrelations -> to test uncorrelated
h <- min(2 * 4, nrow(sales.train)/5) # min(2m, T/5)
Box.test(base.m$residuals, type = "Ljung-Box", lag = h)
```

```
##
## Box-Ljung test
##
## data: base.m$residuals
## X-squared = 9.383, df = 8, p-value = 0.311
```

```
# histogram -> to test zero mean
hist(base.m$residuals, main = "Histogram of residuals (base.m)")
abline(v = mean(base.m$residuals), col = "blue")
# Shapiro-Wilk normality test -> to test normally distributed
shapiro.test(base.m$residuals)
```

```
##
## Shapiro-Wilk normality test
##
## data: base.m$residuals
## W = 0.9649, p-value = 0.07747
```

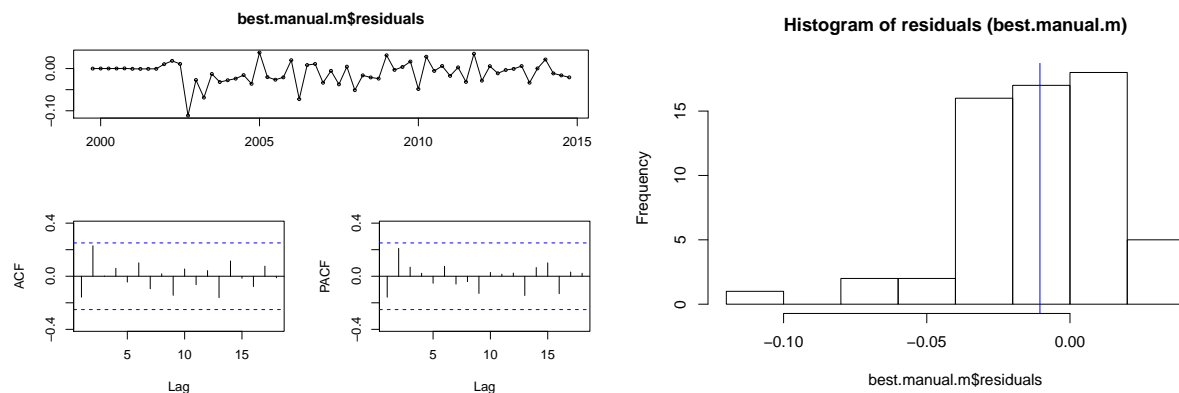


```
# best.manual.m autocorrelations -> to test uncorrelated and view
# variance
tsdisplay(best.manual.m$residuals)
# group of autocorrelations -> to test uncorrelated
h <- min(2 * 4, nrow(sales.train)/5) # min(2m, T/5)
Box.test(best.manual.m$residuals, type = "Ljung-Box", lag = h)
```

```
##
## Box-Ljung test
##
## data: best.manual.m$residuals
## X-squared = 6.7615, df = 8, p-value = 0.5626
```

```
# histogram -> to test zero mean
hist(best.manual.m$residuals, main = "Histogram of residuals (best.manual.m)")
abline(v = mean(best.manual.m$residuals), col = "blue")
# Shapiro-Wilk normality test -> to test normally distributed
shapiro.test(best.manual.m$residuals)
```

```
##
## Shapiro-Wilk normality test
##
## data: best.manual.m$residuals
## W = 0.93326, p-value = 0.002486
```



```

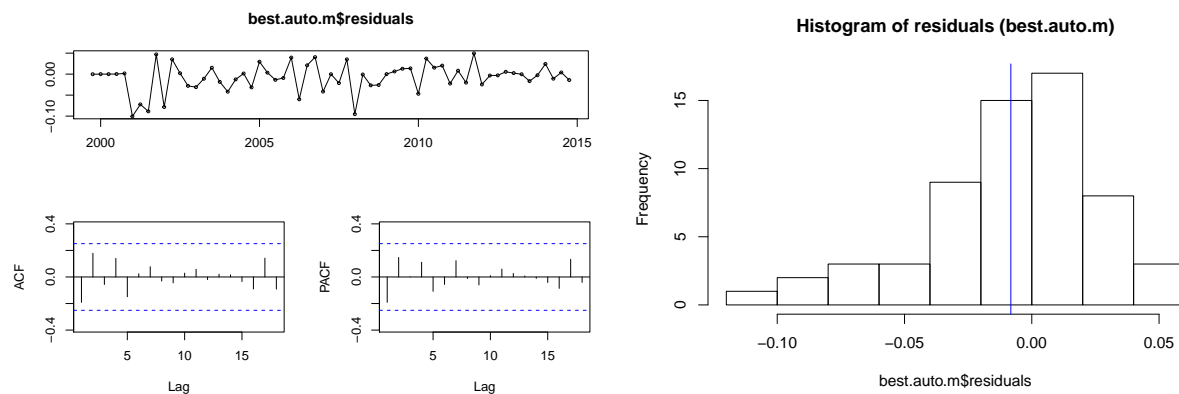
# best.auto.m autocorrelations -> to test uncorrelated and view
# variance
tsdisplay(best.auto.m$residuals)
# group of autocorrelations -> to test uncorrelated
h <- min(2 * 4, nrow(sales.train)/5) # min(2m, T/5)
Box.test(best.auto.m$residuals, type = "Ljung-Box", lag = h)

##
## Box-Ljung test
##
## data: best.auto.m$residuals
## X-squared = 7.9999, df = 8, p-value = 0.4335

# histogram -> to test zero mean
hist(best.auto.m$residuals, main = "Histogram of residuals (best.auto.m)")
abline(v = mean(best.auto.m$residuals), col = "blue")
# Shapiro-Wilk normality test -> to test normally distributed
shapiro.test(best.auto.m$residuals)

##
## Shapiro-Wilk normality test
##
## data: best.auto.m$residuals
## W = 0.93482, p-value = 0.002911

```



Looking at the ACF plots, all spikes of the automated models (best.manual.m, best.auto.m) are within the significant limits, meaning that the residuals are uncorrelated to one another. The same cannot be said about our manually generated model (base.m) with one significant spike at lag 8. We then perform a test on a group of autocorrelations with the Box-Ljung test. The Box-Ljung test validates our assumption that the residuals are uncorrelated. With large p-values, the residuals appear to be uncorrelated for all models. The time plot of the residuals shows that the variation of the residuals stays approximately the same for the three models, so we can treat the residual variance as constant. However, even with a mean close to zero, the histogram of all models suggests that it follows more of a negative skewed distribution than normal. The Shapiro-Wilk test confirms the non-normality of the distribution for the automated models (best.manual.m, best.auto.m) and barely do so for the manually generated one (base.m). What this signifies is that when we perform a



prediction in the following section, its forecast will generally be quite good but prediction intervals computed assuming a normal distribution may be inaccurate.

## Forecasting

Now that we have validated our models, it is time to extrapolate what percentage of e-sales commerce constitutes the total retail sales. First, we compare the forecasts of the two models to the hold out test data from 2015 till 2016 to see if their predictions are comparable to the actual. Then we plot out the forecasts. The blue represents the forecast and the orange represents the test data.

```
sales.test
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 2015  6.9  6.6  6.8  8.7
## 2016  7.7  7.5  7.7  9.5
```

```
InvBoxCox(predict(base.m, 3 * 4)$pred, lambda)
```

```
##      Qtr1      Qtr2      Qtr3      Qtr4
## 2015 6.687957 6.366680 6.564358 8.628952
## 2016 7.512638 7.146104 7.451567 9.813929
## 2017 8.450607 8.148895 8.521327 11.436279
```

```
InvBoxCox(predict(best.manual.m, 3 * 4)$pred, lambda)
```

```
##      Qtr1      Qtr2      Qtr3      Qtr4
## 2015 6.624838 6.279254 6.594150 8.715722
## 2016 7.451578 7.112806 7.497126 10.034900
## 2017 8.534238 8.211646 8.695472 11.796178
```

```
InvBoxCox(predict(best.auto.m, 3 * 4)$pred, lambda)
```

```
##      Qtr1      Qtr2      Qtr3      Qtr4
## 2015 6.705666 6.323977 6.479338 8.392189
## 2016 7.379740 6.930514 7.111839 9.157311
## 2017 8.053882 7.564228 7.761877 9.991076
```

```
ts.plot(cbind(sales.train, sales.test, InvBoxCox(predict(base.m, 4 * 3)$pred,
  lambda)), col = c("black", "orange", "blue"), lty = c(1, 1, 2), main = "Forecasts to 2017 with
```

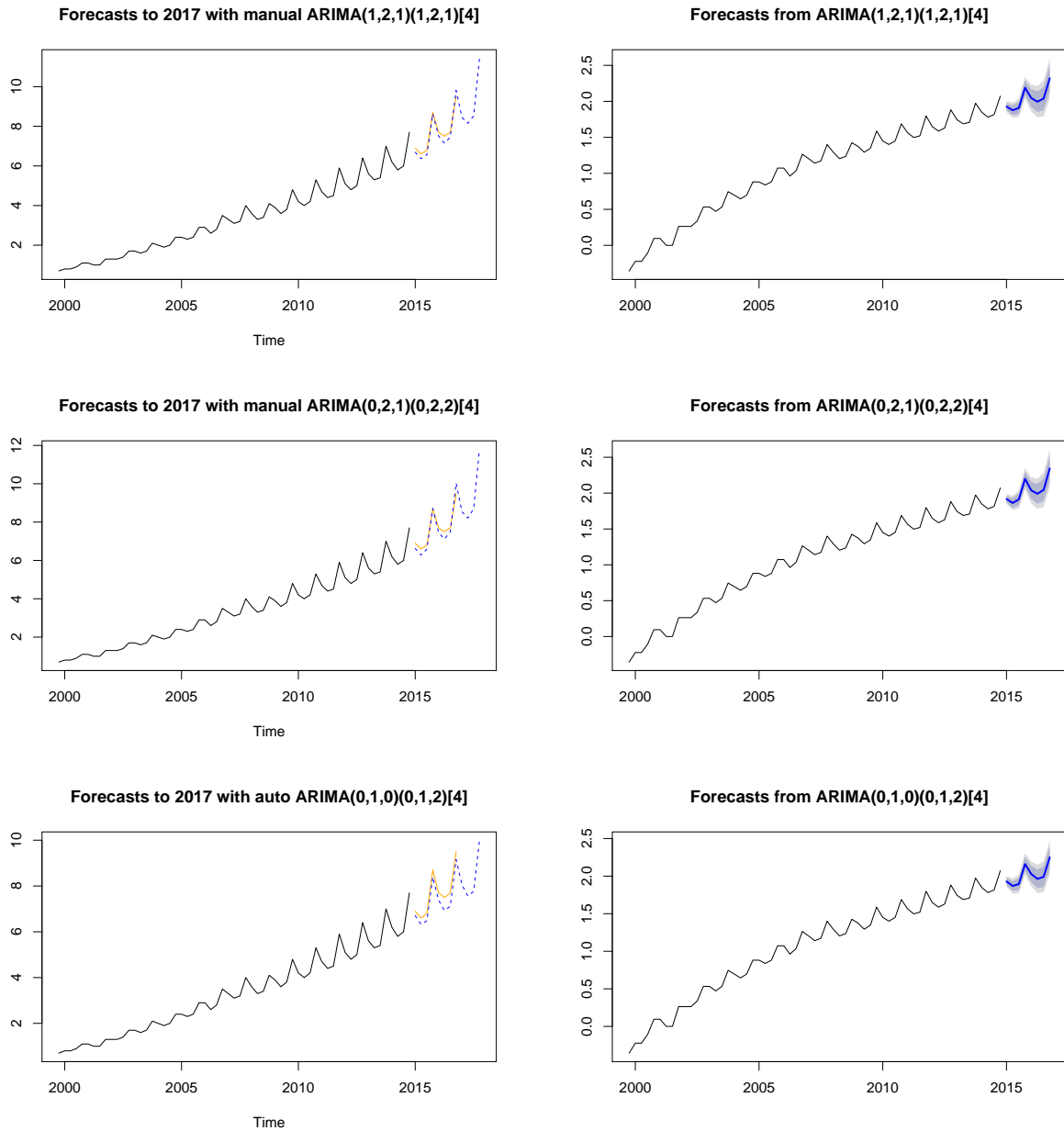
```
plot(forecast(base.m))
```

```
ts.plot(cbind(sales.train, sales.test, InvBoxCox(predict(best.manual.m,
  4 * 3)$pred, lambda)), col = c("black", "orange", "blue"), lty = c(1,
  1, 2), main = "Forecasts to 2017 with manual ARIMA(0,2,1)(0,2,2)[4]")
```

```
plot(forecast(best.manual.m))
```

```
ts.plot(cbind(sales.train, sales.test, InvBoxCox(predict(best.auto.m, 4 *
  3)$pred, lambda)), col = c("black", "orange", "blue"), lty = c(1, 1,
  2), main = "Forecasts to 2017 with auto ARIMA(0,1,0)(0,1,2)[4]")
```

```
plot(forecast(best.auto.m))
```



Both the forecasts as well as the graphs tell us that our manually generated model  $ARIMA(1,2,1)(1,2,1)_4$  predict much more closely to the test data than the automated models. We use our manually generated model to determine that e-commerce makes up approximately 11.44% of all retail sales by the fourth quarter of 2017.

## Question 2: Learning how to use the xts library

If we could select one company to represent the e-commerce trend, Amazon is likely to be the first company that comes to mind.

1. Read AMAZ.csv and UMCSENT.csv into R as R DataFrames.

```
raw.amaz <- read.csv("./data/AMAZ.csv", header = TRUE, sep = ",")
raw.sent <- read.csv("./data/UMCSENT.csv", header = TRUE, sep = ",")
```

```
raw.sent
```

##	Index	UMCSENT
## 1	1978-01-01	83.7
## 2	1978-02-01	84.3
## 3	1978-03-01	78.8
## 4	1978-04-01	81.6
## 5	1978-05-01	82.9
## 6	1978-06-01	80.0
## 7	1978-07-01	82.4
## 8	1978-08-01	78.4
## 9	1978-09-01	80.4
## 10	1978-10-01	79.3
## 11	1978-11-01	75.0
## 12	1978-12-01	66.1
## 13	1979-01-01	72.1
## 14	1979-02-01	73.9
## 15	1979-03-01	68.4
## 16	1979-04-01	66.0
## 17	1979-05-01	68.1
## 18	1979-06-01	65.8
## 19	1979-07-01	60.4
## 20	1979-08-01	64.5
## 21	1979-09-01	66.7
## 22	1979-10-01	62.1
## 23	1979-11-01	63.3
## 24	1979-12-01	61.0
## 25	1980-01-01	67.0
## 26	1980-02-01	66.9
## 27	1980-03-01	56.5
## 28	1980-04-01	52.7
## 29	1980-05-01	51.7
## 30	1980-06-01	58.7
## 31	1980-07-01	62.3
## 32	1980-08-01	67.3
## 33	1980-09-01	73.7
## 34	1980-10-01	75.0
## 35	1980-11-01	76.7
## 36	1980-12-01	64.5
## 37	1981-01-01	71.4
## 38	1981-02-01	66.9
## 39	1981-03-01	66.5
## 40	1981-04-01	72.4
## 41	1981-05-01	76.3
## 42	1981-06-01	73.1

## 43	1981-07-01	74.1
## 44	1981-08-01	77.2
## 45	1981-09-01	73.1
## 46	1981-10-01	70.3
## 47	1981-11-01	62.5
## 48	1981-12-01	64.3
## 49	1982-01-01	71.0
## 50	1982-02-01	66.5
## 51	1982-03-01	62.0
## 52	1982-04-01	65.5
## 53	1982-05-01	67.5
## 54	1982-06-01	65.7
## 55	1982-07-01	65.4
## 56	1982-08-01	65.4
## 57	1982-09-01	69.3
## 58	1982-10-01	73.4
## 59	1982-11-01	72.1
## 60	1982-12-01	71.9
## 61	1983-01-01	70.4
## 62	1983-02-01	74.6
## 63	1983-03-01	80.8
## 64	1983-04-01	89.1
## 65	1983-05-01	93.3
## 66	1983-06-01	92.2
## 67	1983-07-01	92.8
## 68	1983-08-01	90.9
## 69	1983-09-01	89.9
## 70	1983-10-01	89.3
## 71	1983-11-01	91.1
## 72	1983-12-01	94.2
## 73	1984-01-01	100.1
## 74	1984-02-01	97.4
## 75	1984-03-01	101.0
## 76	1984-04-01	96.1
## 77	1984-05-01	98.1
## 78	1984-06-01	95.5
## 79	1984-07-01	96.6
## 80	1984-08-01	99.1
## 81	1984-09-01	100.9
## 82	1984-10-01	96.3
## 83	1984-11-01	95.7
## 84	1984-12-01	92.9
## 85	1985-01-01	96.0
## 86	1985-02-01	93.7
## 87	1985-03-01	93.7
## 88	1985-04-01	94.6
## 89	1985-05-01	91.8
## 90	1985-06-01	96.5

## 91	1985-07-01	94.0
## 92	1985-08-01	92.4
## 93	1985-09-01	92.1
## 94	1985-10-01	88.4
## 95	1985-11-01	90.9
## 96	1985-12-01	93.9
## 97	1986-01-01	95.6
## 98	1986-02-01	95.9
## 99	1986-03-01	95.1
## 100	1986-04-01	96.2
## 101	1986-05-01	94.8
## 102	1986-06-01	99.3
## 103	1986-07-01	97.7
## 104	1986-08-01	94.9
## 105	1986-09-01	91.9
## 106	1986-10-01	95.6
## 107	1986-11-01	91.4
## 108	1986-12-01	89.1
## 109	1987-01-01	90.4
## 110	1987-02-01	90.2
## 111	1987-03-01	90.8
## 112	1987-04-01	92.8
## 113	1987-05-01	91.1
## 114	1987-06-01	91.5
## 115	1987-07-01	93.7
## 116	1987-08-01	94.4
## 117	1987-09-01	93.6
## 118	1987-10-01	89.3
## 119	1987-11-01	83.1
## 120	1987-12-01	86.8
## 121	1988-01-01	90.8
## 122	1988-02-01	91.6
## 123	1988-03-01	94.6
## 124	1988-04-01	91.2
## 125	1988-05-01	94.8
## 126	1988-06-01	94.7
## 127	1988-07-01	93.4
## 128	1988-08-01	97.4
## 129	1988-09-01	97.3
## 130	1988-10-01	94.1
## 131	1988-11-01	93.0
## 132	1988-12-01	91.9
## 133	1989-01-01	97.9
## 134	1989-02-01	95.4
## 135	1989-03-01	94.3
## 136	1989-04-01	91.5
## 137	1989-05-01	90.7
## 138	1989-06-01	90.6

##	139	1989-07-01	92.0
##	140	1989-08-01	89.6
##	141	1989-09-01	95.8
##	142	1989-10-01	93.9
##	143	1989-11-01	90.9
##	144	1989-12-01	90.5
##	145	1990-01-01	93.0
##	146	1990-02-01	89.5
##	147	1990-03-01	91.3
##	148	1990-04-01	93.9
##	149	1990-05-01	90.6
##	150	1990-06-01	88.3
##	151	1990-07-01	88.2
##	152	1990-08-01	76.4
##	153	1990-09-01	72.8
##	154	1990-10-01	63.9
##	155	1990-11-01	66.0
##	156	1990-12-01	65.5
##	157	1991-01-01	66.8
##	158	1991-02-01	70.4
##	159	1991-03-01	87.7
##	160	1991-04-01	81.8
##	161	1991-05-01	78.3
##	162	1991-06-01	82.1
##	163	1991-07-01	82.9
##	164	1991-08-01	82.0
##	165	1991-09-01	83.0
##	166	1991-10-01	78.3
##	167	1991-11-01	69.1
##	168	1991-12-01	68.2
##	169	1992-01-01	67.5
##	170	1992-02-01	68.8
##	171	1992-03-01	76.0
##	172	1992-04-01	77.2
##	173	1992-05-01	79.2
##	174	1992-06-01	80.4
##	175	1992-07-01	76.6
##	176	1992-08-01	76.1
##	177	1992-09-01	75.6
##	178	1992-10-01	73.3
##	179	1992-11-01	85.3
##	180	1992-12-01	91.0
##	181	1993-01-01	89.3
##	182	1993-02-01	86.6
##	183	1993-03-01	85.9
##	184	1993-04-01	85.6
##	185	1993-05-01	80.3
##	186	1993-06-01	81.5

##	187	1993-07-01	77.0
##	188	1993-08-01	77.3
##	189	1993-09-01	77.9
##	190	1993-10-01	82.7
##	191	1993-11-01	81.2
##	192	1993-12-01	88.2
##	193	1994-01-01	94.3
##	194	1994-02-01	93.2
##	195	1994-03-01	91.5
##	196	1994-04-01	92.6
##	197	1994-05-01	92.8
##	198	1994-06-01	91.2
##	199	1994-07-01	89.0
##	200	1994-08-01	91.7
##	201	1994-09-01	91.5
##	202	1994-10-01	92.7
##	203	1994-11-01	91.6
##	204	1994-12-01	95.1
##	205	1995-01-01	97.6
##	206	1995-02-01	95.1
##	207	1995-03-01	90.3
##	208	1995-04-01	92.5
##	209	1995-05-01	89.8
##	210	1995-06-01	92.7
##	211	1995-07-01	94.4
##	212	1995-08-01	96.2
##	213	1995-09-01	88.9
##	214	1995-10-01	90.2
##	215	1995-11-01	88.2
##	216	1995-12-01	91.0
##	217	1996-01-01	89.3
##	218	1996-02-01	88.5
##	219	1996-03-01	93.7
##	220	1996-04-01	92.7
##	221	1996-05-01	89.4
##	222	1996-06-01	92.4
##	223	1996-07-01	94.7
##	224	1996-08-01	95.3
##	225	1996-09-01	94.7
##	226	1996-10-01	96.5
##	227	1996-11-01	99.2
##	228	1996-12-01	96.9
##	229	1997-01-01	97.4
##	230	1997-02-01	99.7
##	231	1997-03-01	100.0
##	232	1997-04-01	101.4
##	233	1997-05-01	103.2
##	234	1997-06-01	104.5

##	235	1997-07-01	107.1
##	236	1997-08-01	104.4
##	237	1997-09-01	106.0
##	238	1997-10-01	105.6
##	239	1997-11-01	107.2
##	240	1997-12-01	102.1
##	241	1998-01-01	106.6
##	242	1998-02-01	110.4
##	243	1998-03-01	106.5
##	244	1998-04-01	108.7
##	245	1998-05-01	106.5
##	246	1998-06-01	105.6
##	247	1998-07-01	105.2
##	248	1998-08-01	104.4
##	249	1998-09-01	100.9
##	250	1998-10-01	97.4
##	251	1998-11-01	102.7
##	252	1998-12-01	100.5
##	253	1999-01-01	103.9
##	254	1999-02-01	108.1
##	255	1999-03-01	105.7
##	256	1999-04-01	104.6
##	257	1999-05-01	106.8
##	258	1999-06-01	107.3
##	259	1999-07-01	106.0
##	260	1999-08-01	104.5
##	261	1999-09-01	107.2
##	262	1999-10-01	103.2
##	263	1999-11-01	107.2
##	264	1999-12-01	105.4
##	265	2000-01-01	112.0
##	266	2000-02-01	111.3
##	267	2000-03-01	107.1
##	268	2000-04-01	109.2
##	269	2000-05-01	110.7
##	270	2000-06-01	106.4
##	271	2000-07-01	108.3
##	272	2000-08-01	107.3
##	273	2000-09-01	106.8
##	274	2000-10-01	105.8
##	275	2000-11-01	107.6
##	276	2000-12-01	98.4
##	277	2001-01-01	94.7
##	278	2001-02-01	90.6
##	279	2001-03-01	91.5
##	280	2001-04-01	88.4
##	281	2001-05-01	92.0
##	282	2001-06-01	92.6



##	283	2001-07-01	92.4
##	284	2001-08-01	91.5
##	285	2001-09-01	81.8
##	286	2001-10-01	82.7
##	287	2001-11-01	83.9
##	288	2001-12-01	88.8
##	289	2002-01-01	93.0
##	290	2002-02-01	90.7
##	291	2002-03-01	95.7
##	292	2002-04-01	93.0
##	293	2002-05-01	96.9
##	294	2002-06-01	92.4
##	295	2002-07-01	88.1
##	296	2002-08-01	87.6
##	297	2002-09-01	86.1
##	298	2002-10-01	80.6
##	299	2002-11-01	84.2
##	300	2002-12-01	86.7
##	301	2003-01-01	82.4
##	302	2003-02-01	79.9
##	303	2003-03-01	77.6
##	304	2003-04-01	86.0
##	305	2003-05-01	92.1
##	306	2003-06-01	89.7
##	307	2003-07-01	90.9
##	308	2003-08-01	89.3
##	309	2003-09-01	87.7
##	310	2003-10-01	89.6
##	311	2003-11-01	93.7
##	312	2003-12-01	92.6
##	313	2004-01-01	103.8
##	314	2004-02-01	94.4
##	315	2004-03-01	95.8
##	316	2004-04-01	94.2
##	317	2004-05-01	90.2
##	318	2004-06-01	95.6
##	319	2004-07-01	96.7
##	320	2004-08-01	95.9
##	321	2004-09-01	94.2
##	322	2004-10-01	91.7
##	323	2004-11-01	92.8
##	324	2004-12-01	97.1
##	325	2005-01-01	95.5
##	326	2005-02-01	94.1
##	327	2005-03-01	92.6
##	328	2005-04-01	87.7
##	329	2005-05-01	86.9
##	330	2005-06-01	96.0

##	331	2005-07-01	96.5
##	332	2005-08-01	89.1
##	333	2005-09-01	76.9
##	334	2005-10-01	74.2
##	335	2005-11-01	81.6
##	336	2005-12-01	91.5
##	337	2006-01-01	91.2
##	338	2006-02-01	86.7
##	339	2006-03-01	88.9
##	340	2006-04-01	87.4
##	341	2006-05-01	79.1
##	342	2006-06-01	84.9
##	343	2006-07-01	84.7
##	344	2006-08-01	82.0
##	345	2006-09-01	85.4
##	346	2006-10-01	93.6
##	347	2006-11-01	92.1
##	348	2006-12-01	91.7
##	349	2007-01-01	96.9
##	350	2007-02-01	91.3
##	351	2007-03-01	88.4
##	352	2007-04-01	87.1
##	353	2007-05-01	88.3
##	354	2007-06-01	85.3
##	355	2007-07-01	90.4
##	356	2007-08-01	83.4
##	357	2007-09-01	83.4
##	358	2007-10-01	80.9
##	359	2007-11-01	76.1
##	360	2007-12-01	75.5
##	361	2008-01-01	78.4
##	362	2008-02-01	70.8
##	363	2008-03-01	69.5
##	364	2008-04-01	62.6
##	365	2008-05-01	59.8
##	366	2008-06-01	56.4
##	367	2008-07-01	61.2
##	368	2008-08-01	63.0
##	369	2008-09-01	70.3
##	370	2008-10-01	57.6
##	371	2008-11-01	55.3
##	372	2008-12-01	60.1
##	373	2009-01-01	61.2
##	374	2009-02-01	56.3
##	375	2009-03-01	57.3
##	376	2009-04-01	65.1
##	377	2009-05-01	68.7
##	378	2009-06-01	70.8

##	379	2009-07-01	66.0
##	380	2009-08-01	65.7
##	381	2009-09-01	73.5
##	382	2009-10-01	70.6
##	383	2009-11-01	67.4
##	384	2009-12-01	72.5
##	385	2010-01-01	74.4
##	386	2010-02-01	73.6
##	387	2010-03-01	73.6
##	388	2010-04-01	72.2
##	389	2010-05-01	73.6
##	390	2010-06-01	76.0
##	391	2010-07-01	67.8
##	392	2010-08-01	68.9
##	393	2010-09-01	68.2
##	394	2010-10-01	67.7
##	395	2010-11-01	71.6
##	396	2010-12-01	74.5
##	397	2011-01-01	74.2
##	398	2011-02-01	77.5
##	399	2011-03-01	67.5
##	400	2011-04-01	69.8
##	401	2011-05-01	74.3
##	402	2011-06-01	71.5
##	403	2011-07-01	63.7
##	404	2011-08-01	55.8
##	405	2011-09-01	59.5
##	406	2011-10-01	60.8
##	407	2011-11-01	63.7
##	408	2011-12-01	69.9
##	409	2012-01-01	75.0
##	410	2012-02-01	75.3
##	411	2012-03-01	76.2
##	412	2012-04-01	76.4
##	413	2012-05-01	79.3
##	414	2012-06-01	73.2
##	415	2012-07-01	72.3
##	416	2012-08-01	74.3
##	417	2012-09-01	78.3
##	418	2012-10-01	82.6
##	419	2012-11-01	82.7
##	420	2012-12-01	72.9
##	421	2013-01-01	73.8
##	422	2013-02-01	77.6
##	423	2013-03-01	78.6
##	424	2013-04-01	76.4
##	425	2013-05-01	84.5
##	426	2013-06-01	84.1

##	427	2013-07-01	85.1
##	428	2013-08-01	82.1
##	429	2013-09-01	77.5
##	430	2013-10-01	73.2
##	431	2013-11-01	75.1
##	432	2013-12-01	82.5
##	433	2014-01-01	81.2
##	434	2014-02-01	81.6
##	435	2014-03-01	80.0
##	436	2014-04-01	84.1
##	437	2014-05-01	81.9
##	438	2014-06-01	82.5
##	439	2014-07-01	81.8
##	440	2014-08-01	82.5
##	441	2014-09-01	84.6
##	442	2014-10-01	86.9
##	443	2014-11-01	88.8
##	444	2014-12-01	93.6
##	445	2015-01-01	98.1
##	446	2015-02-01	95.4
##	447	2015-03-01	93.0
##	448	2015-04-01	95.9
##	449	2015-05-01	90.7
##	450	2015-06-01	96.1
##	451	2015-07-01	93.1
##	452	2015-08-01	91.9
##	453	2015-09-01	87.2
##	454	2015-10-01	90.0
##	455	2015-11-01	91.3
##	456	2015-12-01	92.6
##	457	2016-01-01	92.0
##	458	2016-02-01	91.7
##	459	2016-03-01	91.0
##	460	2016-04-01	89.0
##	461	2016-05-01	94.7
##	462	2016-06-01	93.5
##	463	2016-07-01	90.0
##	464	2016-08-01	89.8
##	465	2016-09-01	91.2
##	466	2016-10-01	87.2
##	467	2016-11-01	93.8
##	468	2016-12-01	98.2
##	469	2017-01-01	98.5
##	470	2017-02-01	96.3
##	471	2017-03-01	96.9
##	472	2017-04-01	97.0
##	473	2017-05-01	97.1
##	474	2017-06-01	95.1

```
## 475 2017-07-01    93.4
## 476 2017-08-01    96.8
## 477 2017-09-01    95.1
```

2. Convert them to xts objects.

```
# set local timezone
Sys.setenv(TZ = "America/Los_Angeles")
# assume stock data is collected in EST
amaz <- xts(raw.amaz[, -1], order.by = as.POSIXct(raw.amaz[, 1], tz = "EST"))
# assume sentiment data is collected in EST
sent <- xts(raw.sent[, -1], order.by = as.POSIXct(raw.sent[, 1], tz = "EST"))

ats <- amaz
uts <- sent
```

3. Merge the two set of series together, preserving all of the observations in both set of series.

a. Fill all of the missing values of the UMCSENT series with -9999.

```
UMCSENT <- merge(ats, uts, join = "outer", fill = -9999)
# head(UMCSENT) tail(UMCSENT) describe(UMCSENT)
```

b. Then create a new series, named UMCSENT02, from the original UMCSENT series and replace all

```
UMCSENT02 <- UMCSENT
UMCSENT02[UMCSENT02 == -9999] <- NA
head(UMCSENT02)
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

```
##           AMAZ.Open  AMAZ.High  AMAZ.Low  AMAZ.Close  AMAZ.Volume  uts
## 1978-01-01         NA         NA         NA         NA         NA 83.7
## 1978-02-01         NA         NA         NA         NA         NA 84.3
## 1978-03-01         NA         NA         NA         NA         NA 78.8
## 1978-04-01         NA         NA         NA         NA         NA 81.6
## 1978-05-01         NA         NA         NA         NA         NA 82.9
## 1978-06-01         NA         NA         NA         NA         NA 80.0
```

c. Then create a new series, named UMCSENT03, and replace the NAs with the last observation.

```
UMCSENT03 <- UMCSENT02
UMCSENT03 <- na.locf(UMCSENT03, na.rm = TRUE, fromLast = TRUE)
# head(UMCSENT03) describe(UMCSENT03)
UMCSENT03["2007-01-03"]
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

```
##           AMAZ.Open  AMAZ.High  AMAZ.Low  AMAZ.Close  AMAZ.Volume  uts
## 2007-01-03         20         20         16         16         650 91.3
```

```
UMCSENT02["2007-01-03"]
```

```
## Warning: timezone of object (EST) is different than current timezone
```

```
## (America/Los_Angeles).
```

```
##          AMAZ.Open AMAZ.High AMAZ.Low AMAZ.Close AMAZ.Volume uts
## 2007-01-03         20         20         16         16         650  NA
```

d. Then create a new series, named UMCSENT04, and replace the NAs using linear interpolation.

```
UMCSENT04 <- UMCSENT02
UMCSENT04 <- na.approx(UMCSENT04, maxgap = 31)
head(UMCSENT04)
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

```
##          AMAZ.Open AMAZ.High AMAZ.Low AMAZ.Close AMAZ.Volume  uts
## 1978-01-01         NA         NA         NA         NA         NA 83.7
## 1978-02-01         NA         NA         NA         NA         NA 84.3
## 1978-03-01         NA         NA         NA         NA         NA 78.8
## 1978-04-01         NA         NA         NA         NA         NA 81.6
## 1978-05-01         NA         NA         NA         NA         NA 82.9
## 1978-06-01         NA         NA         NA         NA         NA 80.0
```

```
# Check if values for uts were replaced
UMCSENT04["2007-01-03"]
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

```
##          AMAZ.Open AMAZ.High AMAZ.Low AMAZ.Close AMAZ.Volume    uts
## 2007-01-03         20         20         16         16         650 96.53871
UMCSENT02["2007-01-03"]
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

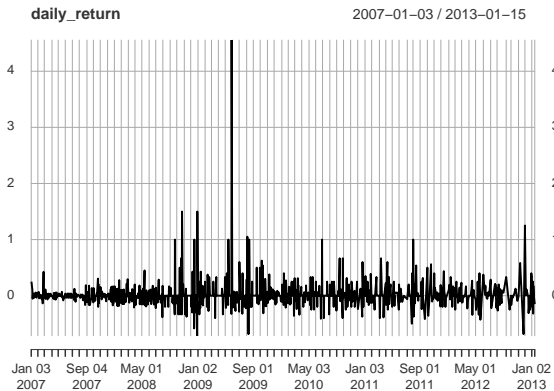
```
##          AMAZ.Open AMAZ.High AMAZ.Low AMAZ.Close AMAZ.Volume uts
## 2007-01-03         20         20         16         16         650  NA
```

e. Print out some observations to ensure that your merge as well as the missing value imputation

```
# TODO!!!!!!!
```

4. Calculate the daily return of the Amazon closing price (AMAZ.close), where daily return is defined as  $(x(t) - x(t - 1))/x(t - 1)$ . Plot the daily return series.

```
daily_return <- (ats[, 4] - lag(ats[, 4], k = 1))/(lag(ats[, 4], k = 1))
plot(daily_return)
```



5. Create a 20-day and a 50-day rolling mean series from the AMAZ.close series.

```
head(cbind(ats[, 4], rollapply(ats[, 4], 20, FUN = mean, na.rm = TRUE)),
      30)
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

##	AMAZ.Close	AMAZ.Close.1
## 2007-01-03	16.0	NA
## 2007-01-04	20.0	NA
## 2007-01-08	22.0	NA
## 2007-01-09	20.8	NA
## 2007-01-10	20.8	NA
## 2007-01-11	21.6	NA
## 2007-01-12	22.0	NA
## 2007-01-16	21.2	NA
## 2007-01-17	21.6	NA
## 2007-01-22	22.8	NA
## 2007-01-23	22.8	NA
## 2007-01-26	22.0	NA
## 2007-01-29	23.2	NA
## 2007-01-31	24.0	NA
## 2007-02-01	24.0	NA
## 2007-02-02	24.0	NA
## 2007-02-05	25.6	NA
## 2007-02-06	24.4	NA
## 2007-02-09	23.6	NA
## 2007-02-12	23.2	22.28
## 2007-02-13	23.6	22.66
## 2007-02-14	23.6	22.84
## 2007-02-15	23.6	22.92
## 2007-02-16	22.4	23.00
## 2007-02-20	20.8	23.00
## 2007-02-21	20.4	22.94
## 2007-02-22	17.6	22.72

```
## 2007-02-23      16.0      22.46
## 2007-02-26      22.8      22.52
## 2007-02-27      22.0      22.48
```

```
head(cbind(ats[, 4], rollapply(ats[, 4], 50, FUN = mean, na.rm = TRUE)),
      60)
```

```
## Warning: timezone of object (EST) is different than current timezone
## (America/Los_Angeles).
```

```
##          AMAZ.Close AMAZ.Close.1
## 2007-01-03      16.00      NA
## 2007-01-04      20.00      NA
## 2007-01-08      22.00      NA
## 2007-01-09      20.80      NA
## 2007-01-10      20.80      NA
## 2007-01-11      21.60      NA
## 2007-01-12      22.00      NA
## 2007-01-16      21.20      NA
## 2007-01-17      21.60      NA
## 2007-01-22      22.80      NA
## 2007-01-23      22.80      NA
## 2007-01-26      22.00      NA
## 2007-01-29      23.20      NA
## 2007-01-31      24.00      NA
## 2007-02-01      24.00      NA
## 2007-02-02      24.00      NA
## 2007-02-05      25.60      NA
## 2007-02-06      24.40      NA
## 2007-02-09      23.60      NA
## 2007-02-12      23.20      NA
## 2007-02-13      23.60      NA
## 2007-02-14      23.60      NA
## 2007-02-15      23.60      NA
## 2007-02-16      22.40      NA
## 2007-02-20      20.80      NA
## 2007-02-21      20.40      NA
## 2007-02-22      17.60      NA
## 2007-02-23      16.00      NA
## 2007-02-26      22.80      NA
## 2007-02-27      22.00      NA
## 2007-02-28      22.00      NA
## 2007-03-01      22.00      NA
## 2007-03-02      22.80      NA
## 2007-03-05      21.60      NA
## 2007-03-06      24.00      NA
## 2007-03-07      22.80      NA
## 2007-03-09      22.80      NA
## 2007-03-12      23.60      NA
```



## 2007-03-15	22.00	NA
## 2007-03-19	22.00	NA
## 2007-03-20	22.80	NA
## 2007-03-22	22.00	NA
## 2007-03-29	22.80	NA
## 2007-03-30	22.80	NA
## 2007-04-04	22.80	NA
## 2007-04-05	22.40	NA
## 2007-04-09	21.60	NA
## 2007-04-10	20.40	NA
## 2007-04-11	20.00	NA
## 2007-04-12	21.00	22.0520
## 2007-04-13	21.60	22.1640
## 2007-04-16	20.20	22.1680
## 2007-04-17	21.04	22.1488
## 2007-04-18	21.60	22.1648
## 2007-04-19	22.80	22.2048
## 2007-04-20	21.20	22.1968
## 2007-04-24	22.40	22.2048
## 2007-04-26	21.60	22.2128
## 2007-04-27	21.60	22.2128
## 2007-04-30	21.60	22.1888

# 1. ECOMPCTNSA: E-commerce retail sales as a percent of total sales

<https://fred.stlouisfed.org/series/ECOMPCTNSA>