Homework 4

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Written problems:

In this question we look at the relationship between inflation and wage using the monthly data from January 1964 to October 1987. inf is the percentage change in U.S. monthly CPI index times 12 (so as to obtain annualized inflation rate), while wage denotes average monthly nominal wage levels in the U.S. We analyze the time series of wage growth, where gwage is defined as the difference of log wage and log of lagged wage. We run the following two autoregressive regressions.

```
library(Hmisc)
wagedat$month<- wagedat$t-floor((wagedat$t-1)/12)*12
wagedat$L.wage<- Lag(wagedat$wage,1)
wagedat$gwage<- log(wagedat$wage) -log(wagedat$L.wage)
wagedat$L.gwage<-Lag(wagedat$gwage,1)
wagedat$L2.gwage<-Lag(wagedat$gwage,2)
wagedat$L3.gwage<-Lag(wagedat$gwage,3)
summary(lm(gwage~L.gwage+L2.gwage+L3.gwage+factor(month),data=wagedat))
```

```
##
## Call:
## lm(formula = gwage ~ L.gwage + L2.gwage + L3.gwage + factor(month),
##     data = wagedat)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0076483 -0.0021840  0.0000533  0.0017447  0.0102101
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.0059115  0.0006698   8.825  < 2e-16 ***
## L.gwage         -0.0049528  0.0559509  -0.089 0.929530
## L2.gwage         0.1329858  0.0554593   2.398 0.017176 *
## L3.gwage         0.3955631  0.0558820   7.079 1.29e-11 ***
## factor(month)2  -0.0032298  0.0009511  -3.396 0.000788 ***
## factor(month)3  -0.0049978  0.0009452  -5.288 2.58e-07 ***
## factor(month)4  -0.0048099  0.0009384  -5.126 5.69e-07 ***
## factor(month)5  -0.0015137  0.0009051  -1.672 0.095613 .
## factor(month)6  -0.0035052  0.0009292  -3.772 0.000199 ***
## factor(month)7  -0.0050121  0.0009234  -5.428 1.28e-07 ***
## factor(month)8  -0.0059963  0.0009171  -6.538 3.15e-10 ***
## factor(month)9   0.0076530  0.0008966   8.535 1.07e-15 ***
## factor(month)10 -0.0049963  0.0011717  -4.264 2.79e-05 ***
## factor(month)11 -0.0065853  0.0011595  -5.679 3.53e-08 ***
## factor(month)12 -0.0106008  0.0011592  -9.145  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.003053 on 267 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.6301, Adjusted R-squared:  0.6107
## F-statistic: 32.49 on 14 and 267 DF,  p-value: < 2.2e-16
```

a. Interpret the highlighted slope coefficient. If the growth rate of wage 3 months ago was 1 percent higher, we'd expect the growth rate of wage of the current month to be .3955 percent higher, on average. Note that, in this model we are controlling for seasonality.

b. Why are there "4 observations deleted due to missingness"? Since gwage is a variable dependent on a lagged difference we lose one value since the first row will have an unknown lagged value. Furthermore we lose 3 more observations, one for each lag (L, L2, L3).

c. Write down the null hypothesis for testing that the gwage series has no seasonality. Write down the alternative hypothesis as well. $H_0 = \beta_4 = \ldots = \beta_{13} = 0$ where β_4 is the slope coefficient of month 2, and so on and so forth such that β_{13} is the slope coefficient of month 12. In other words, all months have a zero slope coefficient $H_A = \beta_4 + \ldots + \beta_{13} \neq 0$ or, in other words, at least one month has a nonzero slope coefficient.

d.The following table listed the last three months of data (i.e. Aug. 1987, Sept. 1987, and Oct. 1987).

```
cbind(wagedat$t[284:286], wagedat$month[284:286], wagedat$gwage[284:286], wagedat$wage[2
84:286])
```

```
##      [,1] [,2]        [,3] [,4]
## [1,]  284    8 0.003361318 8.94
## [2,]  285    9 0.012229237 9.05
## [3,]  286   10 0.003309405 9.08
```

```
nov <- t(results$coefficients) %*% c(1, wagedat$gwage[286], wagedat$gwage[285], wagedat
$gwage[284], 0,0,0,0,0,0,0,0,0,0,1,0)

dec <- t(results$coefficients) %*% c(1, nov, wagedat$gwage[286], wagedat$gwage[285], 0,0
,0,0,0,0,0,0,0,0,0,1)
```

Predict the wage growth (gwage) in Nov. 1987 and Dec. 1987.

Nov. 1987: 0.0022657
Dec. 1987: 5.769866410^{-4}

e. What does the following R output tell us?

```
bgtest(results)
```

```
##
##  Breusch-Godfrey test for serial correlation of order up to 1
##
## data:  results
## LM test = 0.46361, df = 1, p-value = 0.4959
```

With a p-value of .4959, we fail to reject the null hypothesis of no serial correlation at the 5% significance level.

Computer Problems

```
library(tidyverse)
library(forecast)
library(lmtest)
load("~/Desktop/Spring2020/ECN 190/Data/DavisWeather.RData")
glimpse(DavisWeather)
```

```
## Rows: 730
## Columns: 7
## $ date    <date> 2017-01-01, 2017-01-02, 2017-01-03, 2017-01-04, 2017-01-05, …
## $ precip  <dbl> 0.00, 0.00, 0.67, 1.05, 0.16, 0.00, 0.96, 1.74, 1.58, 0.97, 1…
## $ maxtemp <dbl> 51, 51, 50, 54, 49, 46, 59, 60, 58, 57, 57, 50, 57, 53, 51, 5…
## $ mintemp <dbl> 40, 40, 44, 43, 35, 33, 32, 56, 50, 42, 48, 44, 34, 34, 36, 3…
## $ year    <dbl> 2017, 2017, 2017, 2017, 2017, 2017, 2017, 2017, 2017, 2017, 2…
## $ month   <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1…
## $ day     <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18…
```

Computer problems:

This question continues to use the Davis temperature data used in HW3.

1. Focus on year 2017. Construct a deseasonalized maximum temperature time series of year 2017.

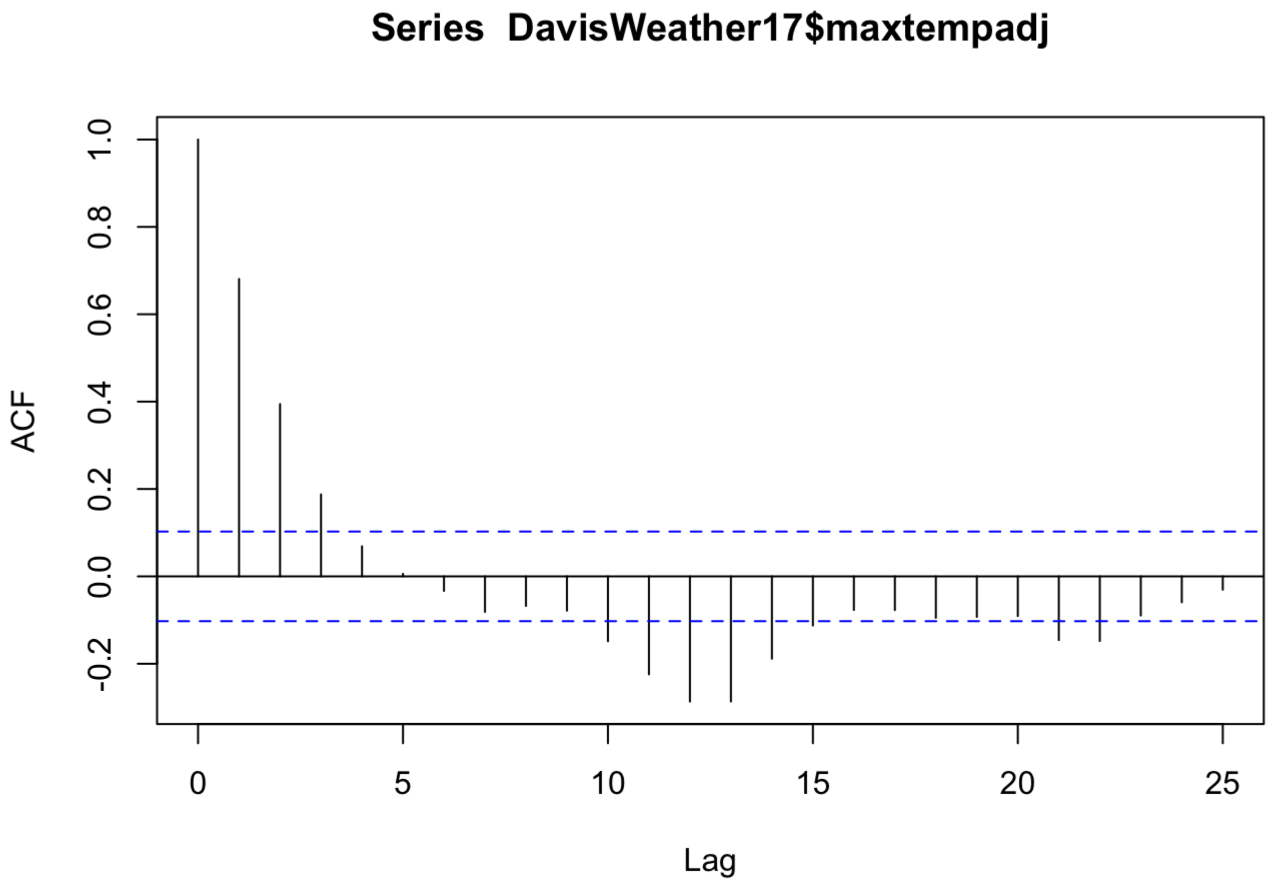
```
DavisWeather17 <- DavisWeather %>%
  filter(year == 2017)
results<-lm(maxtemp~factor(month),data=DavisWeather17)
summary(results)
```

```
##
## Call:
## lm(formula = maxtemp ~ factor(month), data = DavisWeather17)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.567  -3.710   0.250   3.645  20.267
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)       54.355      1.174  46.286  < 2e-16 ***
## factor(month)2     5.395      1.705   3.165  0.00169 **
## factor(month)3    14.645      1.661   8.818  < 2e-16 ***
## factor(month)4    16.978      1.675  10.139  < 2e-16 ***
## factor(month)5    29.161      1.661  17.559  < 2e-16 ***
## factor(month)6    36.212      1.675  21.625  < 2e-16 ***
## factor(month)7    41.806      1.661  25.173  < 2e-16 ***
## factor(month)8    40.290      1.661  24.260  < 2e-16 ***
## factor(month)9    35.378      1.675  21.127  < 2e-16 ***
## factor(month)10   27.355      1.661  16.471  < 2e-16 ***
## factor(month)11   10.278      1.675   6.138 2.25e-09 ***
## factor(month)12    7.484      1.661   4.506 8.98e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.538 on 353 degrees of freedom
## Multiple R-squared:  0.8272, Adjusted R-squared:  0.8218
## F-statistic: 153.6 on 11 and 353 DF,  p-value: < 2.2e-16
```

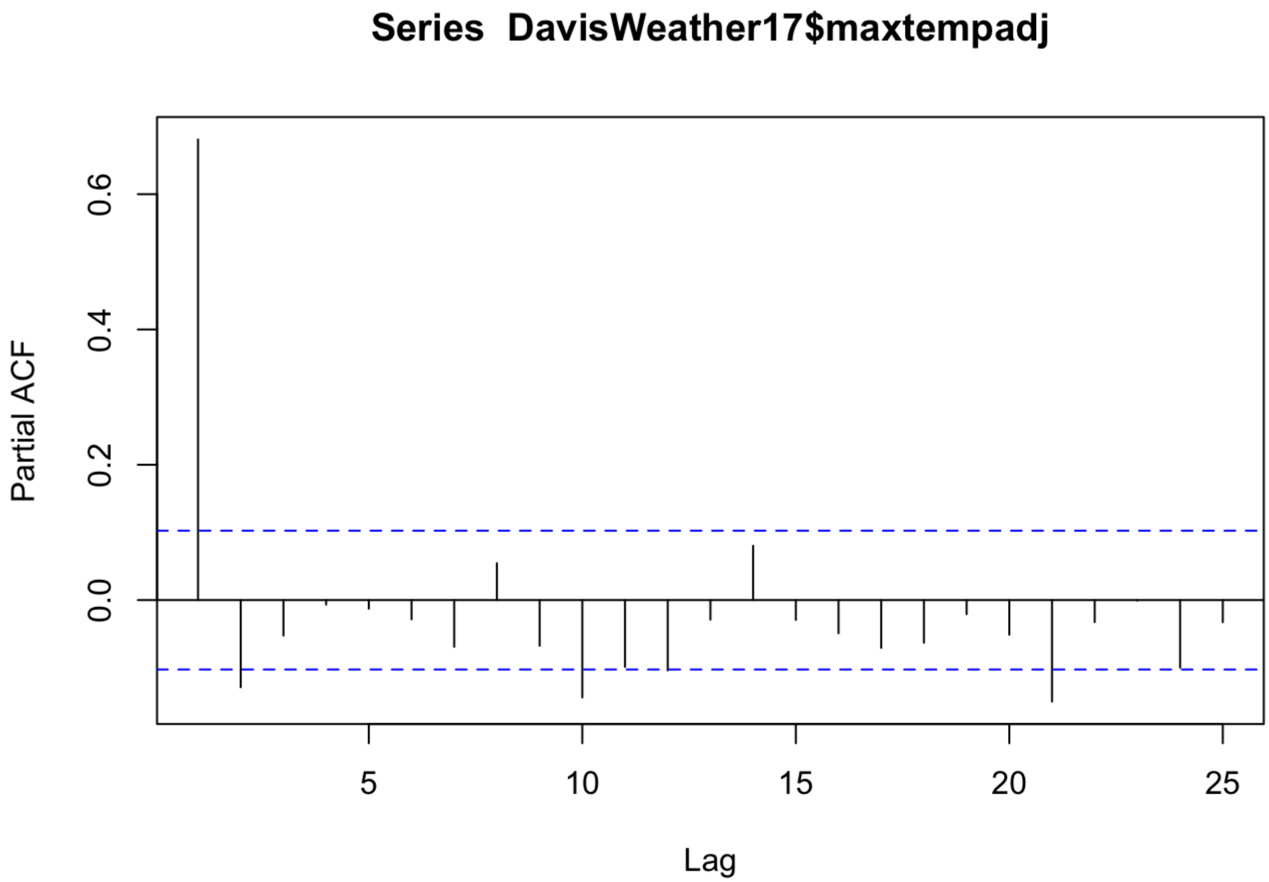
```
DavisWeather17 <- DavisWeather17 %>%
  mutate(maxtempadj = residuals(results),
         L.adjmaxtemp = lag(maxtempadj),
         L2.adjmaxtemp = lag(maxtempadj, 2))
```

2. Plot the autocorrelation graph of the deseasonalized maximum temperature time series of year 2017. Then plot the partial autocorrelation graph.

```
acf(DavisWeather17$maxtempadj)
```




```
pacf(DavisWeather17$maxtempadj)
```



These two graphs indicate that the ARMA(2,1) model would be appropriate since the acf graph has a graudal decline and the pacf has a sharp drop off.

3. Run an AR(1) regression using the deseasonalized maximum temperature time series of year 2017. Then test for the assumption of no serial correlation using the Breusch- Godfrey test.

```
DavisWeather17$ARpredictmaxtemp <- c(NA, lm(maxtempadj ~ L.adjmaxtemp + factor(month), d
ata = DavisWeather17) %>%
  predict())
lm(maxtempadj ~ L.adjmaxtemp , data = DavisWeather17) %>%
  bgtest()
```

```
##
##  Breusch-Godfrey test for serial correlation of order up to 1
##
## data:  .
## LM test = 6.0266, df = 1, p-value = 0.01409
```

With a p-value of .014, we reject the null hypothesis of no serial correlation at the 5% significance level.

4. Run an AR(2) regression using the deseasonalized maximum temperature time series of year 2017. Then test for the assumption of no serial correlation using the Breusch- Godfrey test.

```
DavisWeather17$AR2predictmaxtemp <- c(NA, NA,
                                     lm(maxtempadj ~ L.adjmaxtemp + L2.adjmaxtemp + fact
or(month),
                                        data = DavisWeather17) %>%
                                       predict())
lm(maxtempadj ~ L.adjmaxtemp + L2.adjmaxtemp, data = DavisWeather17) %>%
  bgtest()
```

```
##
##  Breusch-Godfrey test for serial correlation of order up to 1
##
## data:  .
## LM test = 1.0522, df = 1, p-value = 0.305
```

With a p-value of .305, we fail to reject the null hypothesis of no serial correlation at the 5% significance level.

5. Now, fit the deseasonalized maximum temperature time series of year 2017 with an ARIMA(p,d,q) model. Use the “auto.arima” command in the “forecast” package to automatically pick p, d, and q. What regression model does the R command end up picking for this time series?

```
results <- auto.arima(DavisWeather17$maxtempadj)
results
```

```
## Series: DavisWeather17$maxtempadj
## ARIMA(2,0,1) with zero mean
##
## Coefficients:
##          ar1      ar2      ma1
##       1.6522  -0.7019  -0.9892
## s.e.  0.0370   0.0369   0.0104
##
## sigma^2 estimated as 20.8:  log likelihood=-1071.36
## AIC=2150.72   AICc=2150.83   BIC=2166.32
```

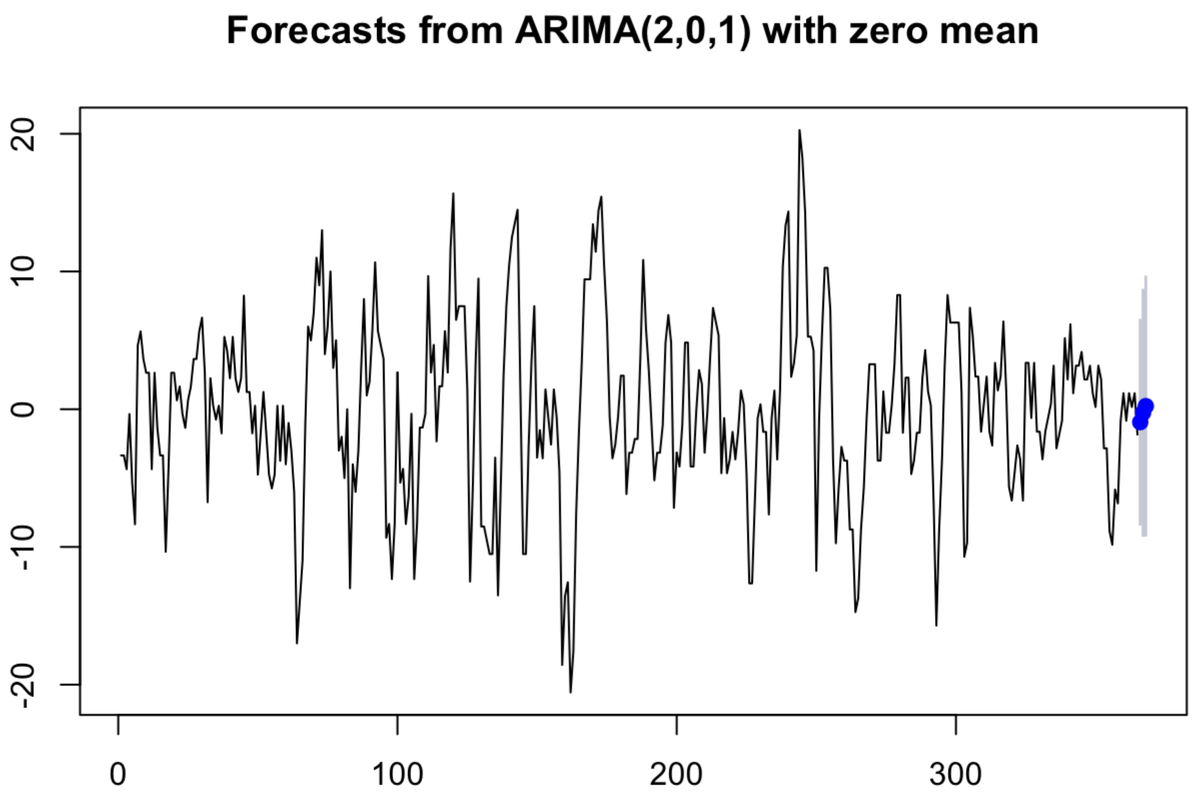
The model produced using the `auto.arima` function is ARMA(2, 1).

6. Use the “forecast” command in the “forecast” package to forecast the deseasonalized maximum temperature of Jan. 1-3, 2018 using the model you obtained in the last question. Note that these are the deseasonalized time series. How would you forecast the raw maximum temperature of Jan. 1-3, 2018?

```
fcast <- forecast(results, h = 3, level = 90); fcast
```

```
##     Point Forecast     Lo 90    Hi 90
## 366     -0.9401883 -8.441790 6.561413
## 367     -0.2628302 -9.263289 8.737629
## 368      0.2256515 -9.246479 9.697782
```

```
plot(fcast)
```



I would use the `auto.arima` function using the raw maximum temperatures to forecast the raw maximum temperatures of Jan. 1-3, 2018.

```
results <- auto.arima(DavisWeather17$maxtemp); results
```

```
## Series: DavisWeather17$maxtemp
## ARIMA(1,1,2)
##
## Coefficients:
##          ar1      ma1      ma2
##       0.6518  -0.7578  -0.1309
## s.e.  0.0723   0.0813   0.0612
##
## sigma^2 estimated as 23.03:  log likelihood=-1086.09
## AIC=2180.18   AICc=2180.29   BIC=2195.77
```

```
fcast <- forecast(results, h = 3, level = 90); fcast
```

```
##     Point Forecast    Lo 90    Hi 90
## 366       59.89029 51.99685 67.78374
## 367       60.16946 49.58157 70.75736
## 368       60.35143 48.43033 72.27252
```

```
plot(fcast)
```