Econ 211C HW 3

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Number 1

a

6/2/2017

```
gam0<-17.5170
gam1<-15.9570
gam2<-12.4010
gam3<-8.3985
gam4<-5.0576
gam5<-3.0155

vec1<-c(gam0,gam1,gam2,gam3,gam4)
vec2<-c(gam1,gam0,gam1,gam2,gam3)
vec3<-c(gam2,gam1,gam0,gam1,gam2)
vec4<-c(gam3,gam2,gam1,gam0,gam1)
vec5<-c(gam4,gam3,gam2,gam1,gam0)</pre>
colvec<-t(c(gam1,gam2,gam3,gam4,gam5))
mat1<-rbind(vec1,vec2,vec3,vec4,vec5)
betas<-solve(mat1)%*%t(colvec)</pre>
```

b/c

```
#b
func1<-function(n){</pre>
phi < -c(1.3, -0.4)
theta<-c(0.7,0,0.1,-0.5,-0.2)
p<-length(phi)</pre>
q<-length(theta)</pre>
r<-max(p,q)
err<-rnorm(n+r,0,1)
y<-rep(0,n+r)
for( i in (r+1):(r+n)){
      y[i]<-err[i]+t(phi)%*%y[(i-1):(i-p)]+t(theta)%*%err[(i-1):(i-q)]
}
y<-y[-(1:r)]
#C
#create new vector containing forecasts
y<-func1(105)
forecastvec<-rep(0,5)</pre>
forecastvec[1]<-betas[1]*y[100]+betas[2]*y[99]+betas[3]*y[98]+betas[4]*y[97]+betas[5]*y[96]
forecastvec[2]<-
betas[1]*forecastvec[1]+betas[2]*y[100]+betas[3]*y[99]+betas[4]*y[98]+betas[5]*y[97]
forecast vec \cite{betas} as the construction of the constructio
etas[5]*y[98]
forecastvec[4]<-
betas[1]*forecastvec[3]+betas[2]*forecastvec[2]+betas[3]*forecastvec[1]+betas[4]*y[100]+betas[5]*y
9]
forecastvec[5]<-
betas[1]*forecastvec[4]+betas[2]*forecastvec[3]+betas[3]*forecastvec[2]+betas[4]*forecastvec[1]+b
etas[5]*y[100]
forecastvec
```

```
## [1] -5.1621641 -3.4707394 -1.9364587 -0.9122664 -0.5240398
```

```
meansqerr<-rep(0,1000)
for(i in 1:1000){
       y<-func1(105)
        forecastvec<-rep(0,5)</pre>
        forecastvec[1]<-betas[1]*y[100]+betas[2]*y[99]+betas[3]*y[98]+betas[4]*y[97]+betas[5]*y[96]
        forecastvec[2]<-
betas[1]*forecastvec[1]+betas[2]*y[100]+betas[3]*y[99]+betas[4]*y[98]+betas[5]*y[97]
        forecastvec[3]<-
betas[1]*forecastvec[2]+betas[2]*forecastvec[1]+betas[3]*y[100]+betas[4]*y[99]+betas[5]*y[98]
        forecastvec[4]<-
betas[1]*forecastvec[3]+betas[2]*forecastvec[2]+betas[3]*forecastvec[1]+betas[4]*y[100]+betas[5]*y
9]
        forecastvec[5]<-
betas [1]*forecast vec [4]+betas [2]*forecast vec [3]+betas [3]*forecast vec [2]+betas [4]*forecast vec [1]+betas [2]+betas [4]+betas 
etas[5]*y[100]
        meansqerr[i]<-(forecastvec[5]-y[105])^2</pre>
}
mse<-mean(meansqerr)</pre>
mse
```

[1] 17.55869

d/e

```
#d

autocov<-c(gam0,gam1,gam2,gam3,gam4,gam5,0,0,0,0)
for(i in 7:10){
  autocov[i]<-1.3*autocov[i-1]-0.4*autocov[i-2]
}
vector1<-as.matrix(autocov[6:10],nrow=5)
betas1<-solve(mat1)%*%vector1
betas1</pre>
```

```
## [,1]

## [1,] 0.66058023

## [2,] -0.78791078

## [3,] 0.32258357

## [4,] 0.01081816

## [5,] -0.01471187
```

```
#e
##Five Step Forecast

forecastvec2<-betas1[1]*y[100]+betas1[2]*y[99]+betas1[3]*y[98]+betas1[4]*y[97]+betas1[5]*y[96]
forecastvec2</pre>
```

```
## [1] 0.4438863
```

f

```
### 5 Step Squared Error

meansqerr5<-rep(0,1000)
for(i in 1:1000){
    y<-func1(105)
    forecastvec2<-betas1[1]*y[100]+betas1[2]*y[99]+betas1[3]*y[98]+betas1[4]*y[97]+betas1[5]*y[96]
    meansqerr5<-(forecastvec2-y[105])^2
}

mean(meansqerr5)
```

```
## [1] 1.706941
```

g

```
#### Same procedure but using coef from arima

library(forecast)

y<-func1(105)
reg1<-arima(y[1:100],order=c(2,0,5))
reg1</pre>
```

```
##
## Call:
  arima(x = y[1:100], order = c(2, 0, 5))
##
## Coefficients:
##
           ar1
                    ar2
                            ma1
                                    ma2
                                            ma3
                                                    ma4
                                                            ma5 intercept
##
        0.7971 -0.4997 0.9656 1.0880 1.2443 0.6587 0.5367
                                                                    0.2963
        0.1554
                 0.1477 0.1375 0.1997 0.1511 0.1633 0.1537
                                                                    0.6875
## s.e.
##
## sigma^2 estimated as 0.8025: log likelihood = -134.74, aic = 287.49
```

h

```
### obtain the coefficients from the regression

phi<-c(reg1$coef[1],reg1$coef[2])
theta<-c(reg1$coef[3],reg1$coef[4],reg1$coef[5],reg1$coef[6],reg1$coef[7])

#Autcorrelations
autos<-ARMAacf(ar=phi,ma=theta,lag.max=10)
#Autocovs
autocovs<-autos*var(y)

col1<-c(autocovs[1],autocovs[2],autocovs[3],autocovs[4],autocovs[5])
col2<-c(autocovs[2],autocovs[1],autocovs[2],autocovs[3],autocovs[4])
col3<-c(autocovs[3],autocovs[2],autocovs[1],autocovs[2],autocovs[3])
col4<-c(autocovs[4],autocovs[3],autocovs[2],autocovs[1],autocovs[2])
col5<-c(autocovs[5],autocovs[4],autocovs[3],autocovs[2],autocovs[1])

mat2<-rbind(col1,col2,col3,col4,col5)
mat2</pre>
```

```
## col1 11.9336823 10.508048 7.238084 3.490709 0.5379844
## col2 10.5080480 11.933682 10.508048 7.238084 3.4907090
## col3 7.2380840 10.508048 11.933682 10.508048 7.2380840
## col4 3.4907090 7.238084 10.508048 11.933682 10.5080480
## col5 0.5379844 3.490709 7.238084 10.508048 11.9336823
```

```
gams<-matrix(c(autocovs[2],autocovs[3],autocovs[4],autocovs[5],autocovs[6]),nrow=5)
gams</pre>
```

```
## [,1]

## [1,] 10.5080480

## [2,] 7.2380840

## [3,] 3.4907090

## [4,] 0.5379844

## [5,] -0.8564702
```

```
betas2<-solve(mat2)%*%gams
betas2</pre>
```

```
## [,1]

## 0 1.62375748

## 1 -0.82937963

## 2 -0.01535625

## 3 -0.03333840

## 4 0.13630058
```

I/J

```
###New forecasts
y<-func1(105)
newforecast<-rep(0,5)</pre>
for(i in 1:5){
  newforecast[i]<-
betas2[1]*y[99+i]+betas2[2]*y[98+i]+betas2[3]*y[97+i]+betas2[4]*y[96+i]+betas2[5]*y[95+i]
}
newsqerr<-rep(0,1000)
for(j in 1:1000){
  y<-func1(105)
  for(i in 1:5){
    newforecast[i]<-betas2[1]*y[99+i]+betas2[2]*y[98+i]+betas2[3]*y[97+i]+betas2[4]*y[96+i]+beta
s2[5]*y[95+i]
  }
  newsqerr[j]<-(newforecast[5]-y[105])^2</pre>
mean(newsqerr)
```

[1] 1.338047

```
###
y<-func1(105)
forecast_<-rep(0,5)
forecast_[1]<-betas2[1]*y[100]+betas2[2]*y[99]+betas2[3]*y[98]+betas2[4]*y[97]+betas2[5]*y[96]
forecast_[2]<-
betas2[1]*forecast_[1]+betas2[2]*y[100]+betas2[3]*y[99]+betas2[4]*y[98]+betas2[5]*y[97]
forecast_[3]<-betas2[1]*forecast_[2]+betas2[2]*forecast_[1]+betas2[3]*y[100]+betas[4]*y[99]+beta
s[5]*y[98]
forecast_[4]<-betas2[1]*forecast_[3]+betas2[2]*forecast_[2]+betas2[3]*forecast_[1]+betas2[4]*y[1
00]+betas2[5]*y[99]
forecast_[5]<-betas2[1]*forecast_[4]+betas2[2]*forecast_[3]+betas2[3]*forecast_[2]+betas2[4]*forecast_[1]+betas2[5]*y[100]</pre>
forecast_
```

```
## [1] -1.35400592 -0.87431903 -0.06245055 0.43533973 0.56675185
```

```
anothermeansqerr<-rep(0,1000)
for(i in 1:1000){
             y<-func1(105)
             forecast_<-rep(0,5)</pre>
             forecast_[1]<-betas2[1]*y[100]+betas2[2]*y[99]+betas2[3]*y[98]+betas2[4]*y[97]+betas2[5]*y[96]
             forecast_[2]<-
betas2[1]*forecast_[1]+betas2[2]*y[100]+betas2[3]*y[99]+betas2[4]*y[98]+betas2[5]*y[97]
              forecast_{[3]}<-betas2[1]*forecast_{[2]}+betas2[2]*forecast_{[1]}+betas2[3]*y[100]+betas[4]*y[99]+betas2[2]*forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forecast_{[3]}+forec
tas[5]*y[98]
             forecast_[4]<-
betas 2 [1]*forecast_[3] + betas 2 [2]*forecast_[2] + betas 2 [3]*forecast_[1] + betas 2 [4]*y [100] + betas 2 [5]*y [100] + betas 2 [1]*forecast_[2] + betas 2 [1]*forecast_[3] + be
              forecast_[5]<-betas2[1]*forecast_[4]+betas2[2]*forecast_[3]+betas2[3]*forecast_[2]+betas2[4]*f
orecast_[1]+betas2[5]*y[100]
              anothermeansqerr[i]<-(forecast_[5]-y[105])^2</pre>
}
mean(anothermeansqerr)
```

[1] 22.91601

K/L

```
### Part D again
vec_<-matrix(NA,nrow=5,ncol=1)
for(i in 1:5){
  vec_[i,1]<-autocovs[i+5]
}
betas3<-solve(mat2)%*%vec_
betas3</pre>
```

```
## [,1]

## 0 0.3668678

## 1 -0.8153995

## 2 0.3169569

## 3 0.3342672

## 4 -0.2365998
```

```
anotherforecast<- betas3[1]*y[100]+betas3[2]*y[99]+betas3[3]*y[98]+betas3[4]*y[97]+betas3[5]*y[96] anotherforecast
```

```
## [1] -1.310898
```

```
squarerror<-rep(NA,1000)
for(i in 1:1000){
    y<-func1(105)
    forecastvec_=betas3[1]*y[100]+betas3[2]*y[99]+betas3[3]*y[98]+betas3[4]*y[97]+betas3[5]*y[96]
    squarerror[i]<-(forecast_-y[105])^2
}
mean(squarerror)</pre>
```

```
## [1] 52.31359
```

Number 2

a

```
#a

d<-read.csv("C:/Users/Aj/Documents/UCSC Coursework/Spring Quarter 2017/Econ 211C - Time Series/H
omework/Assignment3Data.csv")
size<-nrow(d)
reg1<-lm(d$Returns[3:size]~d$Returns[2:(size-1)]+d$Returns[1:(size-2)]+d$OrderFlow[2:(size-
1)]+d$OrderFlow[1:(size-2)])
reg2<-lm(d$OrderFlow[3:size]~d$OrderFlow[2:(size-1)]+d$OrderFlow[1:(size-2)]+d$Returns[2:(size-
1)]+d$Returns[1:(size-2)])
summary(reg1)</pre>
```

```
##
## Call:
## lm(formula = d$Returns[3:size] ~ d$Returns[2:(size - 1)] + d$Returns[1:(size -
       2)] + d$OrderFlow[2:(size - 1)] + d$OrderFlow[1:(size - 2)])
##
##
## Residuals:
##
         Min
                     1Q
                            Median
                                           3Q
                                                     Max
## -7.940e-04 -1.120e-04 -8.060e-06 9.688e-05 1.977e-03
##
## Coefficients:
##
                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                             8.057e-06 1.213e-05 0.664
                                                             0.507
                          -5.967e-03 7.470e-02 -0.080
                                                             0.936
## d$Returns[2:(size - 1)]
## d$Returns[1:(size - 2)] 6.708e-02 7.440e-02 0.902
                                                             0.368
## d$OrderFlow[2:(size - 1)] -1.195e-07 1.327e-07 -0.900
                                                             0.369
## d$OrderFlow[1:(size - 2)] -4.342e-08 1.314e-07 -0.331
                                                             0.741
##
## Residual standard error: 0.0002386 on 383 degrees of freedom
## Multiple R-squared: 0.007863, Adjusted R-squared: -0.002499
## F-statistic: 0.7588 on 4 and 383 DF, p-value: 0.5526
```

summary(reg2)

```
##
## Call:
## lm(formula = d$OrderFlow[3:size] ~ d$OrderFlow[2:(size - 1)] +
##
       d$OrderFlow[1:(size - 2)] + d$Returns[2:(size - 1)] + d$Returns[1:(size -
##
      2)])
##
## Residuals:
      Min
               1Q Median
##
                               30
                                      Max
  -599.50 -31.37 -3.97
                            30.41 1403.09
##
## Coefficients:
##
                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                             4.902e+00 6.804e+00
                                                  0.720
                                                            0.472
## d$OrderFlow[2:(size - 1)] -1.079e-01 7.448e-02 -1.449
                                                            0.148
## d$OrderFlow[1:(size - 2)] 5.419e-02 7.370e-02 0.735
                                                            0.463
## d$Returns[2:(size - 1)] 3.619e+04 4.191e+04
                                                   0.863
                                                            0.388
## d$Returns[1:(size - 2)]
                             2.830e+04 4.175e+04
                                                  0.678
                                                            0.498
##
## Residual standard error: 133.9 on 383 degrees of freedom
## Multiple R-squared: 0.01527, Adjusted R-squared: 0.004983
## F-statistic: 1.484 on 4 and 383 DF, p-value: 0.2062
```

C

```
#c
error<-matrix(0,nrow=2,ncol=length(residuals(reg2)))
error[1,]<-residuals(reg1)
error[2,]<-residuals(reg2)

#Variance and Covariance matrix of the residuals and find the eigenvectors
covmat<-matrix(NA,nrow=2,ncol=2)
covmat[1,1]=var(residuals(reg1))
covmat[2,2]=var(residuals(reg2))
covmat[1,2]=cov(residuals(reg1),residuals(reg2))
covmat[2,1]=cov(residuals(reg1),residuals(reg2))</pre>
covmat

covmat
```

```
## [,1] [,2]
## [1,] 5.634283e-08 2.311864e-02
## [2,] 2.311864e-02 1.773753e+04
```

```
eigenvec<-eigen(covmat)
vec_1<-eigenvec$vectors[,1]
vec_2<-eigenvec$vectors[,2]

mat_<-rbind(vec_1,vec_2)

newvec<-t(mat_)%*%error

## Mat_ is the matrix that orthogonalizes the error vector. This gets rid of contemporaneous cor relation.</pre>
```