573_FinalExam

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Question 1

a

Which plot (Left or Right) of the LJung-box statistics suggests autocorrelation exists in the time series.Justify your answer. (2 pts)

The left plot indicates that there is autocorrelation as the different lag values have signifficance below the p value line.

b

What are the null and alternative hypotheses corresponding to the p-value the arrow points to? (3 pts) - Null Hypothesis: there is no autocorrelation up to a a specific lag - Alternative hypothesis: there is some autocorrelation at one or more legs

Question 2

Im assuming here that "quantities" refer to either predicting, filtering, smoothing, and forecasting.It seems that the quantities of interest are defined in the question itself?

a

current position and velocity would be a filtering problem

c (why is this out of order?)

Predicting during the huricane wold be a forecasting problem

b

this would be a smoothing operation

Question 3

Fit HHMM model with two hidden states

```r
library(depmixS4)
```

```
## Warning: package 'depmixS4' was built under R version 4.4.2

## Loading required package: nnet

## Loading required package: MASS

## Loading required package: Rsolnp

## Warning: package 'Rsolnp' was built under R version 4.4.2

## Loading required package: nlme
```

```r
library(astsa)

data(qinfl)

# Build HMM with 2 states and Gaussian emissions
mod <- depmix(response = qinfl ~ 1,
              data = data.frame(qinfl=qinfl),
              nstates = 2,
              family = gaussian())

fitmod <- fit(mod)
```

```
## converged at iteration 18 with logLik: -243.8824
```

```r
# Show parameter estimates
summary(fitmod)
```

```
## Initial state probabilities model
## pr1 pr2
##   0   1
##
## Transition matrix
##         toS1  toS2
## fromS1 0.976 0.024
## fromS2 0.029 0.971
##
## Response parameters
## Resp 1 : gaussian
##     Re1.(Intercept) Re1.sd
## St1           7.860  3.124
## St2           1.902  1.578
```

Fit linear Gaussian state-space model

```
library(MARSS)
```

```
## Warning: package 'MARSS' was built under R version 4.4.2
```

```
data(qinfl)
inflation <- qinfl

Y <- matrix(inflation, nrow = 1)

model.list <- list(
  Z = matrix(1),
  A = matrix(0),
  B = matrix("b1"),
  U = matrix("u1"),
  Q = matrix("q1"),
  R = matrix("r1"),
  x0 = matrix("x0"),
  V0 = matrix("v0")
)


fit_initial <- MARSS(Y, model = model.list, method = "kem")
```

```
## Warning! Abstol convergence only. Maxit (=500) reached before log-log convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## WARNING: Abstol convergence only no log-log convergence.
##  maxit (=500) reached before log-log convergence.
##  The likelihood and params might not be at the ML values.
##  Try setting control$maxit higher.
## Log-likelihood: -215.6751
## AIC: 443.3501   AICc: 444.1656
##
##       Estimate
## R.r1  7.84e-01
## B.b1  9.36e-01
## U.u1  3.46e-01
## Q.q1  1.67e+00
## x0.x0 1.15e-05
## V0.v0 4.38e-03
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
##
## Convergence warnings
##  Warning: the  x0.x0  parameter value has not converged.
##  Type MARSSinfo("convergence") for more info on this warning.
```

```r
fit_final <- MARSS(Y, model = model.list, inits = fit_initial, method = "BFGS")
```

```
## Success! Converged in 10 iterations.
## Function MARSSkfas used for likelihood calculation.
##
## MARSS fit is
## Estimation method: BFGS
## Estimation converged in 10 iterations.
## Log-likelihood: -215.191
## AIC: 442.3819   AICc: 443.1975
##
##       Estimate
## R.r1  8.33e-01
## B.b1  9.44e-01
## U.u1  3.02e-01
## Q.q1  1.57e+00
## x0.x0 1.58e+00
## V0.v0 4.56e-06
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```r
summary(fit_final)
```

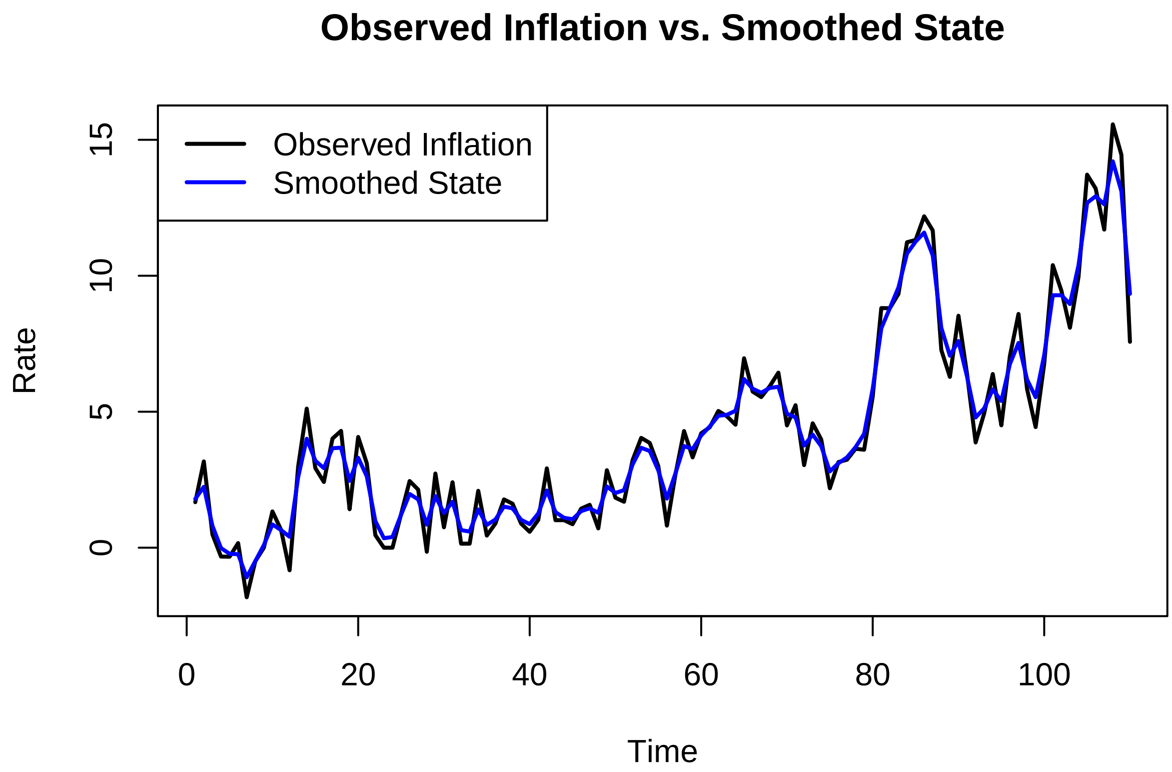
```
##
## m: 1 state process(es) named X.Y1
## n: 1 observation time series named Y1
##
##    term     estimate
## 1  R.r1 8.328455e-01
## 2  B.b1 9.438911e-01
## 3  U.u1 3.019168e-01
## 4  Q.q1 1.570584e+00
## 5 x0.x0 1.581683e+00
## 6 V0.v0 4.557436e-06
```

```r
states = fit_final$states
time_index <- seq_along(qinfl)

states <- as.numeric(fit_final$states)
qinfl_data <- as.numeric(qinfl)

plot.ts(qinfl_data, type = "l", col = "black", lwd = 2,
        ylab = "Rate",
        main = "Observed Inflation vs. Smoothed State")
lines(states, col = "blue", lwd = 2)

legend("topleft", legend = c("Observed Inflation", "Smoothed State"),
       col = c("black", "blue"), lwd = 2)
```



This is similar to stochastic regression as it allows for the relationships to vary with time instead of being set.

c

HMM assumes that the process swaps between discrete spaces with specific feature sets while gaussian state assumes that the evolution is continual.

d

Stochastic Regression

```
library(MARSS)
data(qinfl)
data(qintr)

len <- length(qinfl)
Z <- array(NA, c(1, 2, len))
Z[1, 1, ] <- 1
Z[1, 2, ] <- qintr

model_list <- list(
  B = diag(2),
  U = "zero",
  A = matrix(0,1,1),
```

```r
  Q = "diagonal and unequal",
  Z = Z,
  R = matrix("r",1,1),
  x0 = matrix(c("x01","x02"), 2, 1),
  V0 = diag(0.01, 2),
  tinitx = 0
)

inits <- list(
  x0 = matrix(c(0, 0), 2, 1)
)

fit_init <- MARSS(qinfl, model=model_list, method="kem", inits=inits)
```

```
## Warning! Abstol convergence only. Maxit (=500) reached before log-log convergence.
##
## MARSS fit is
## Estimation method: kem
## Convergence test: conv.test.slope.tol = 0.5, abstol = 0.001
## WARNING: Abstol convergence only no log-log convergence.
##  maxit (=500) reached before log-log convergence.
##  The likelihood and params might not be at the ML values.
##  Try setting control$maxit higher.
## Log-likelihood: -201.4763
## AIC: 412.9526   AICc: 413.5295
##
##           Estimate
## R.r       1.467358
## Q.(X1,X1) 0.004689
## Q.(X2,X2) 0.013585
## x0.x01    0.000149
## x0.x02    0.000686
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
##
## Convergence warnings
##  Warning: the  Q.(X1,X1)  parameter value has not converged.
##  Type MARSSinfo("convergence") for more info on this warning.
```

```r
fit_final <- MARSS(qinfl, model=model_list, method="BFGS", inits=fit_init)
```

```
## Success! Converged in 12 iterations.
## Function MARSSkfas used for likelihood calculation.
##
## MARSS fit is
## Estimation method: BFGS
## Estimation converged in 12 iterations.
## Log-likelihood: -197.801
## AIC: 405.602   AICc: 406.179
##
```

```
##             Estimate
## R.r         1.53e+00
## Q.(X1,X1)  5.65e-11
## Q.(X2,X2)  8.11e-03
## x0.x01    -8.43e-01
## x0.x02     1.12e+00
## Initial states (x0) defined at t=0
##
## Standard errors have not been calculated.
## Use MARSSparamCIs to compute CIs and bias estimates.
```

```r
summary(fit_final)
```

```
##
## m: 2 state process(es) named X1 X2
## n: 1 observation time series named Y1
##
##        term      estimate
## 1       R.r  1.534416e+00
## 2 Q.(X1,X1)  5.648406e-11
## 3 Q.(X2,X2)  8.109504e-03
## 4    x0.x01 -8.430630e-01
## 5    x0.x02  1.121526e+00
```

e

in model d, inflation is described by another observed variable with a time varying slope. this is not available in model b.

f

This really depends on how you view inflation and its relation to time. I would personally choose the final model as it has a better view of the general macroeconomic enviroment with the incorporation of interest rate.