

Centro de Estatística Aplicada

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```
library(forecast)
library(randtests)
```

```
##
## Attaching package: 'randtests'

## The following object is masked from 'package:tseries':
##
## runs.test
```

```
library(zoo)
library(TSA)
```

```
## Registered S3 methods overwritten by 'TSA':
##   method      from
##   fitted.Arima forecast
##   plot.Arima   forecast

##
## Attaching package: 'TSA'

## The following object is masked from 'package:GeneCycle':
##
##   periodogram

## The following object is masked from 'package:readr':
##
##   spec

## The following objects are masked from 'package:stats':
##
##   acf, arima

## The following object is masked from 'package:utils':
##
##   tar
```

```
library(gridExtra)
library(FitAR)
```

```
## Loading required package: lattice

##
## Attaching package: 'lattice'

## The following object is masked from 'package:faraway':
##
##   melanoma
```

```
## Loading required package: leaps

## Loading required package: ltsa

## Loading required package: bestglm

##
## Attaching package: 'FitAR'

## The following object is masked from 'package:forecast':
##
##      BoxCox

## The following object is masked from 'package:car':
##
##      Boot
```

```
library(glmnet)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##      expand, pack, unpack

## Loaded glmnet 4.1-1
```

```
library(islasso)
library(astsa)
```

```
##
## Attaching package: 'astsa'

## The following objects are masked from 'package:fma':
##
##      chicken, sales

## The following object is masked from 'package:forecast':
##
##      gas

## The following object is masked from 'package:fpp2':
##
##      oil
```

```
## The following object is masked from 'package:faraway':
##
##      star

## The following object is masked from 'package:gamlss.data':
##
##      oil
```

```
library(lmtest)
library(forecast)
```

Análise das séries temporais mensais

Análise Descritiva

```
data$Data <- as.Date(data$Data)
head(data)
```

```
## # A tibble: 6 x 24
##   Data      Arroz 'Avicultura de ~ 'Avicultura de ~ Banana Batata
##   <date>      <dbl>      <dbl>      <dbl> <dbl> <dbl>
## 1 2007-01-01  0.01          0.295          3.43 -2.86  0.75
## 2 2007-02-01 -0.68          1.71          2.82 -1.62 -3.83
## 3 2007-03-01 -0.635         2.26         10.1   1.05  7.61
## 4 2007-04-01 -0.635        -0.56          1.31 -2.65 36.4
## 5 2007-05-01  0.13         -0.13         -1.11 -1.46 11.6
## 6 2007-06-01  0.230          0.27          4.93 -1.07 -5.17
## # ... with 18 more variables: Bovinocultura <dbl>, 'Cacau e produtos' <dbl>,
## #   Café <dbl>, Cebola <dbl>, 'Complexo soja' <dbl>, 'Complexo
## #   sucroalc.' <dbl>, Feijão <dbl>, Frutas <dbl>, Hortícolas <dbl>,
## #   Indefinido <dbl>, 'Laranja e citros' <dbl>, Lácteos <dbl>, Mandioca <dbl>,
## #   Milho <dbl>, Pescado <dbl>, Suinocultura <dbl>, Tomate <dbl>, Trigo <dbl>
```

```
zt2 <- ts(data[,2], frequency = 12, start = 2007, end = 2019)
zt3 <- ts(data[,3], frequency = 12, start = 2007, end = 2019)
zt4 <- ts(data[,4], frequency = 12, start = 2007, end = 2019)
zt5 <- ts(data[,5], frequency = 12, start = 2007, end = 2019)
zt6 <- ts(data[,6], frequency = 12, start = 2007, end = 2019)
zt7 <- ts(data[,7], frequency = 12, start = 2007, end = 2019)
zt8 <- ts(data[,8], frequency = 12, start = 2007, end = 2019)
zt9 <- ts(data[,9], frequency = 12, start = 2007, end = 2019)
zt10 <- ts(data[,10], frequency = 12, start = 2007, end = 2019)
zt11 <- ts(data[,11], frequency = 12, start = 2007, end = 2019)

zt12 <- ts(data[,12], frequency = 12, start = 2007, end = 2019)
zt13 <- ts(data[,13], frequency = 12, start = 2007, end = 2019)
zt14 <- ts(data[,14], frequency = 12, start = 2007, end = 2019)
zt15 <- ts(data[,15], frequency = 12, start = 2007, end = 2019)
```

```

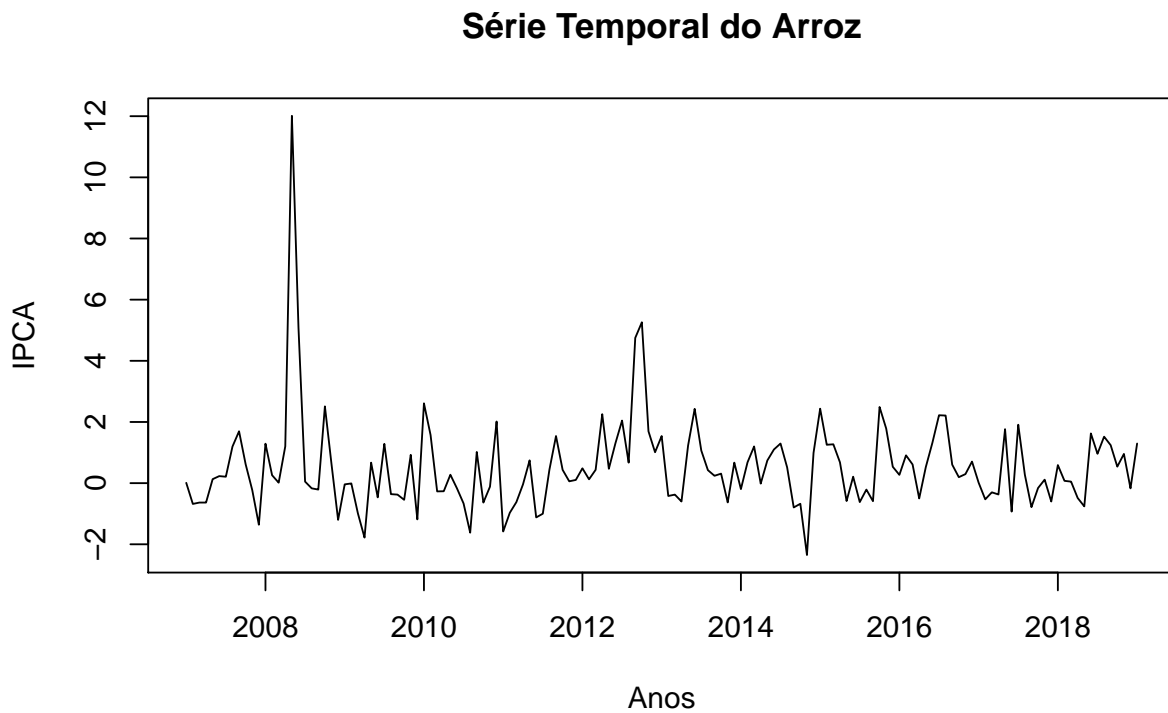
zt16 <- ts(data[,16], frequency = 12, start = 2007, end = 2019)
zt17 <- ts(data[,17], frequency = 12, start = 2007, end = 2019)
zt18 <- ts(data[,18], frequency = 12, start = 2007, end = 2019)
zt19 <- ts(data[,19], frequency = 12, start = 2007, end = 2019)
zt20 <- ts(data[,20], frequency = 12, start = 2007, end = 2019)
zt21 <- ts(data[,21], frequency = 12, start = 2007, end = 2019)
zt22 <- ts(data[,22], frequency = 12, start = 2007, end = 2019)
zt23 <- ts(data[,23], frequency = 12, start = 2007, end = 2019)
zt24 <- ts(data[,24], frequency = 12, start = 2007, end = 2019)

```

```

plot(zt2,main="Série Temporal do Arroz", xlab= "Anos", ylab="IPCA")

```

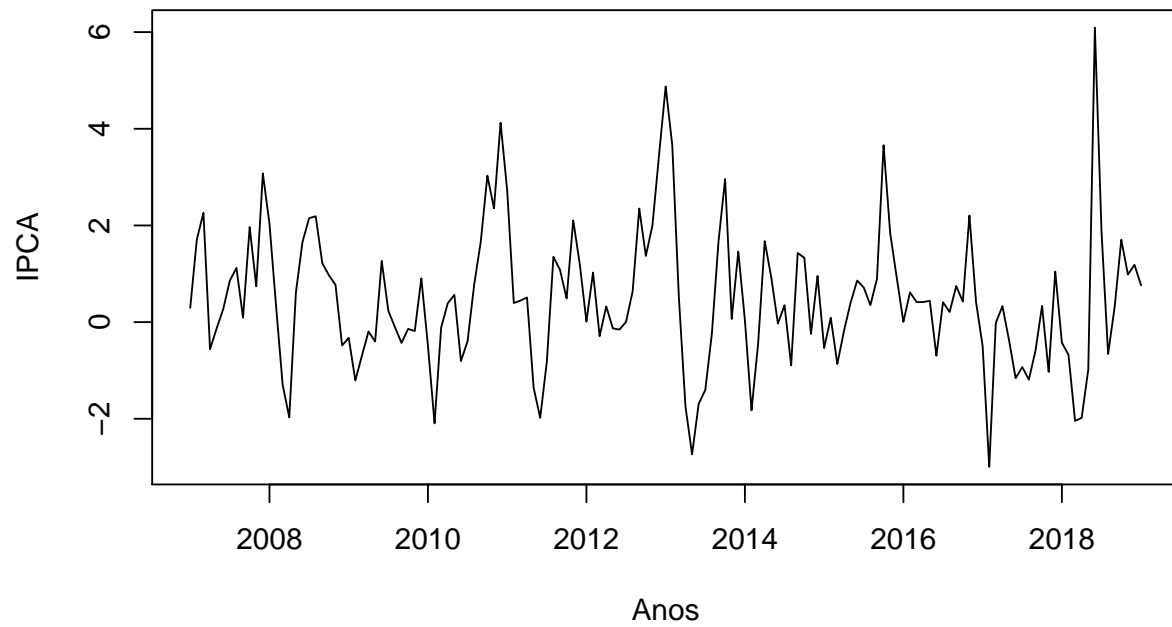


```

#par(mfrow = c(2, 2))
plot(zt3,main="Série Temporal de Avicultura de Corte", xlab= "Anos", ylab="IPCA")

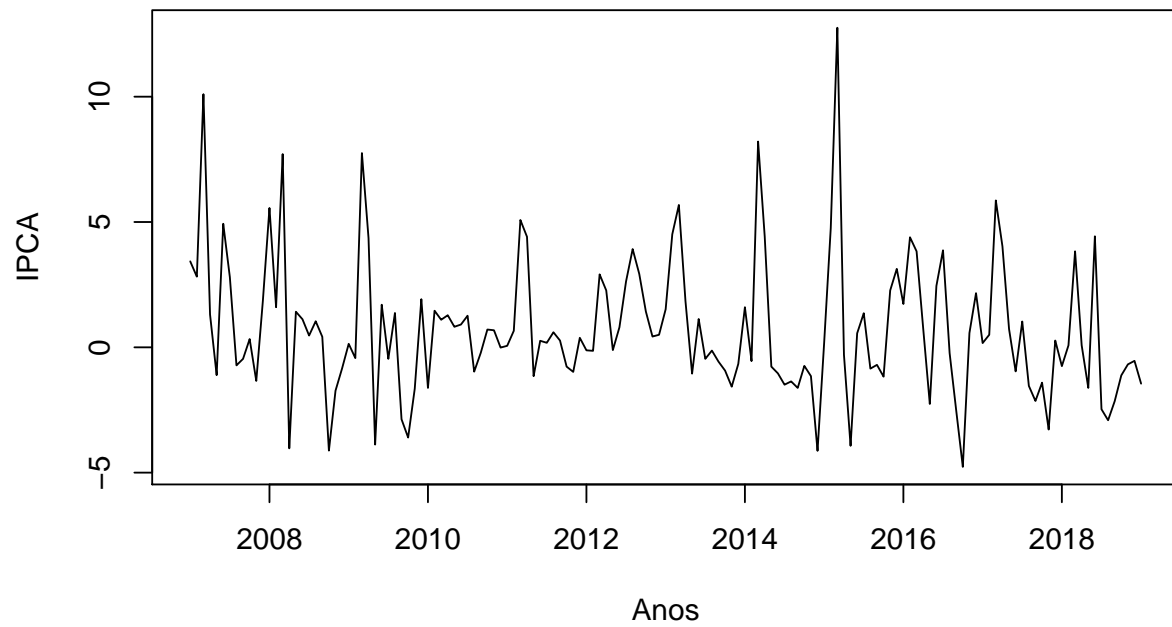
```

Série Temporal de Avicultura de Corte



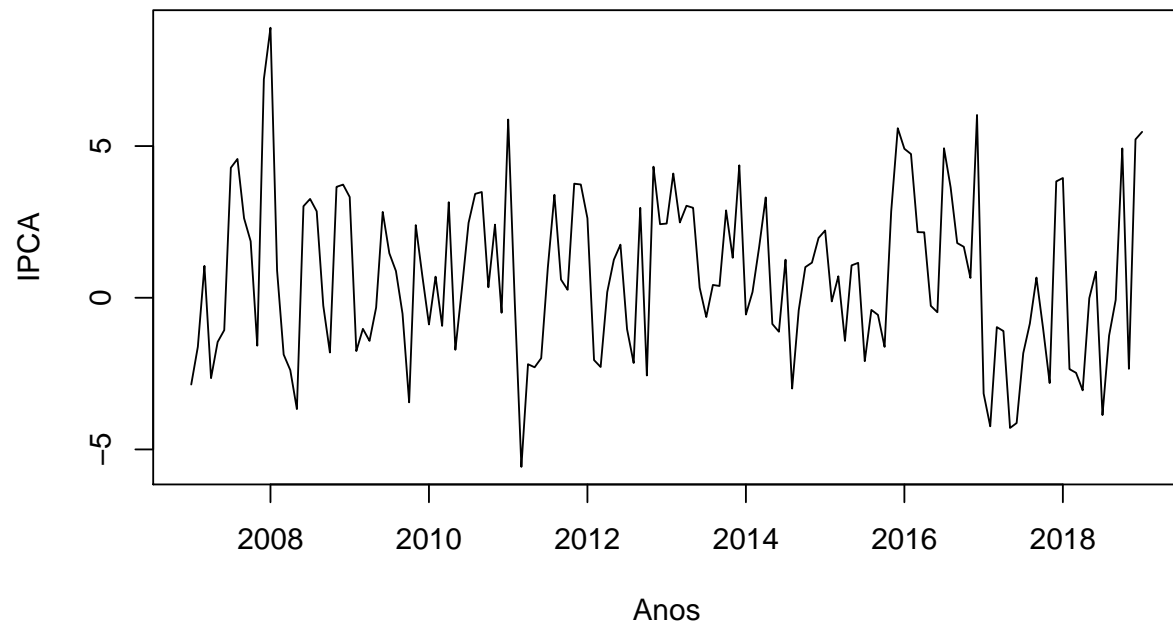
```
plot(zt4,main="Série Temporal de Avicultura de Postura", xlab= "Anos", ylab="IPCA")
```

Série Temporal de Avicultura de Postura



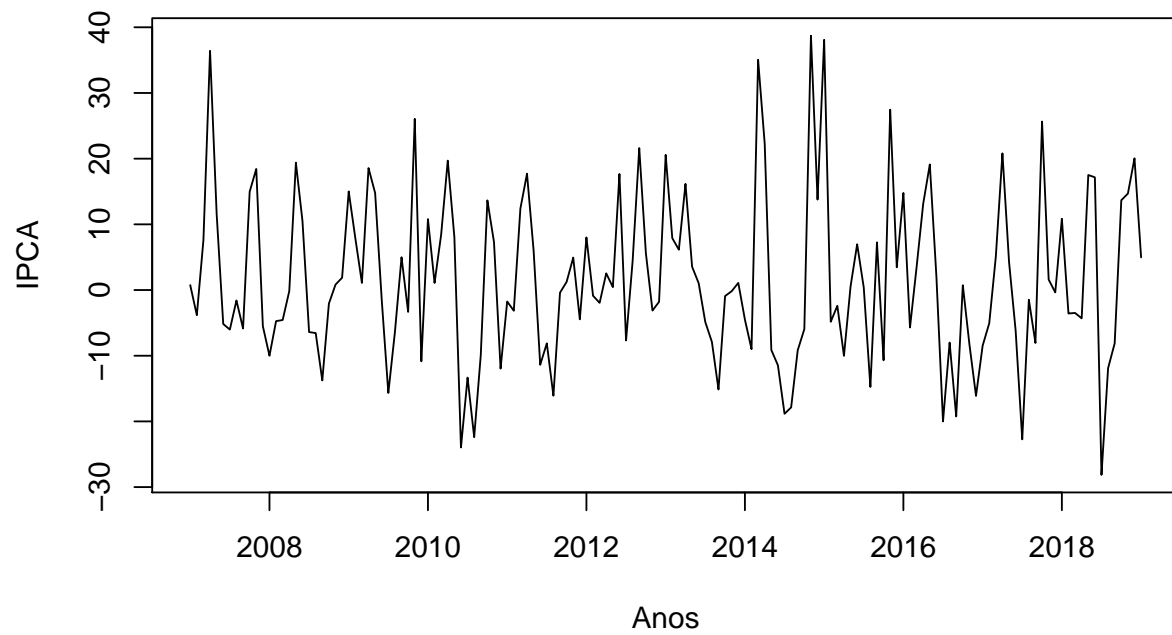
```
plot(zt5,main="Série Temporal da Banana", xlab= "Anos", ylab="IPCA")
```

Série Temporal da Banana



```
plot(zt6,main="Série Temporal da Batata", xlab= "Anos", ylab="IPCA")
```

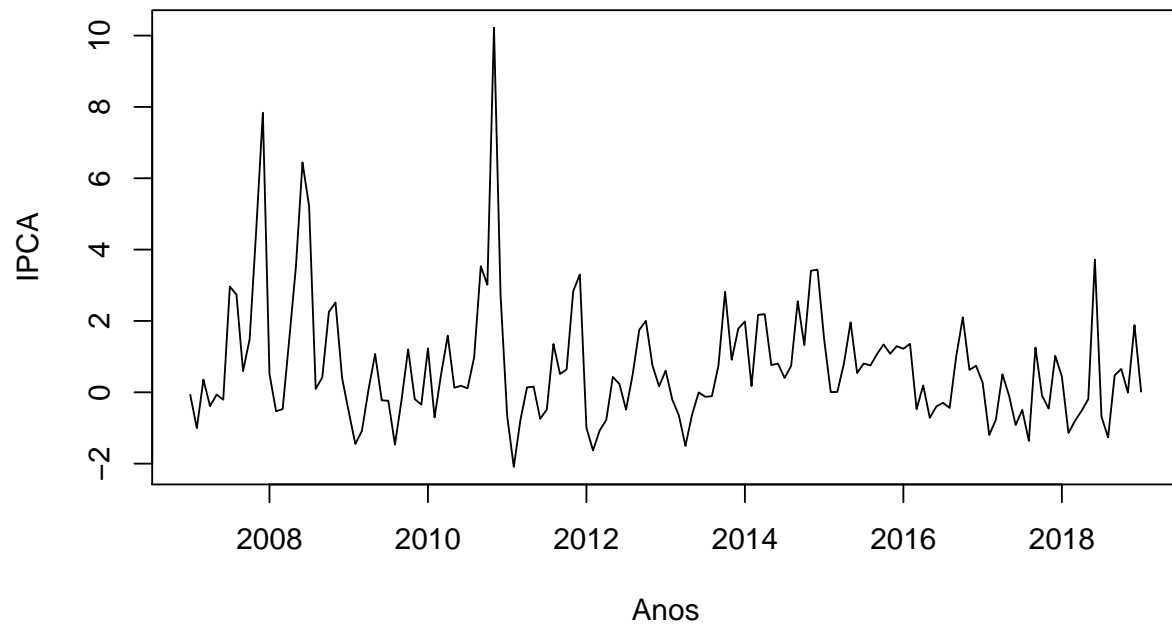

Série Temporal da Batata



```
#par(mfrow = c(3, 2))
```

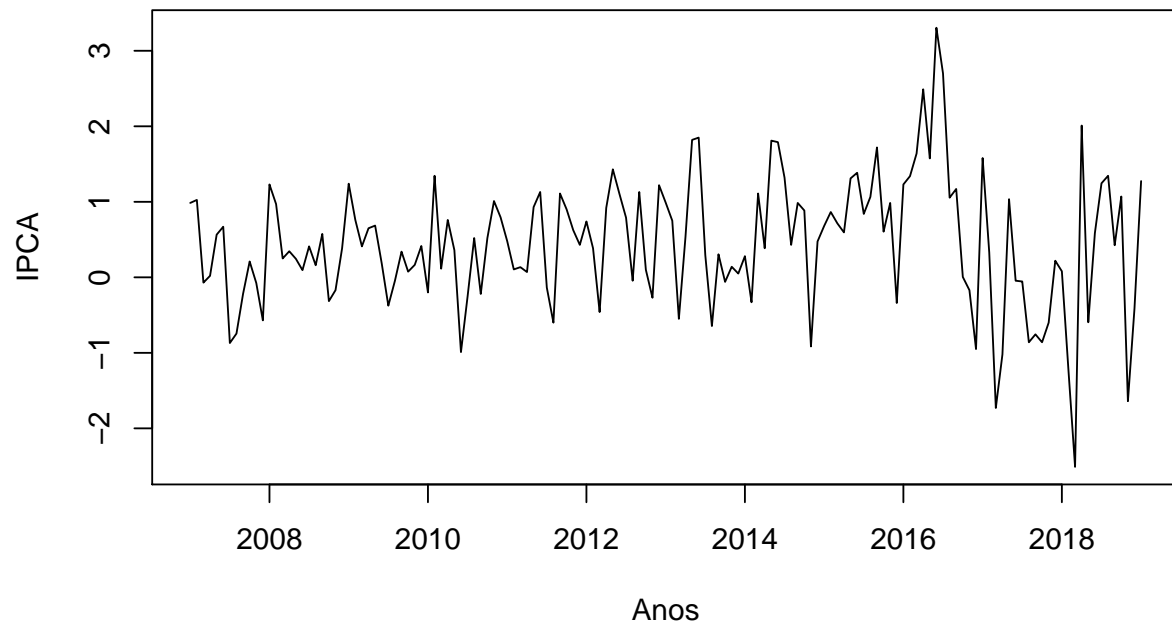
```
plot(zt7,main="Série Temporal da Bovinocultura", xlab= "Anos", ylab="IPCA")
```

Série Temporal da Bovinocultura



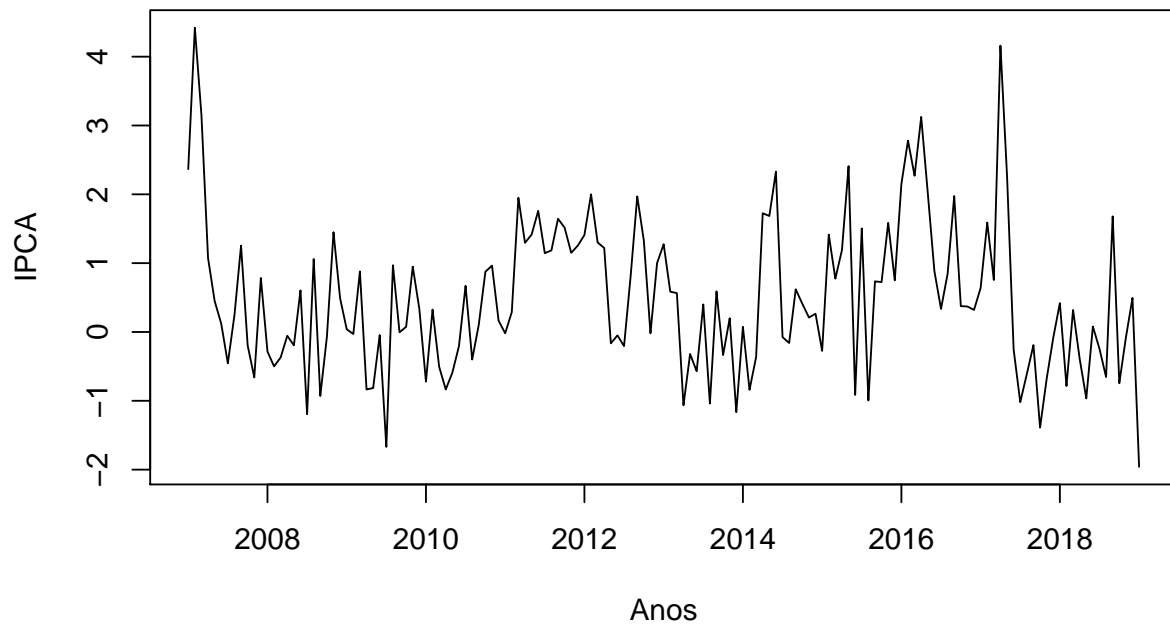
```
plot(zt8,main="Série Temporal do Cacau e Produtos", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Cacau e Produtos



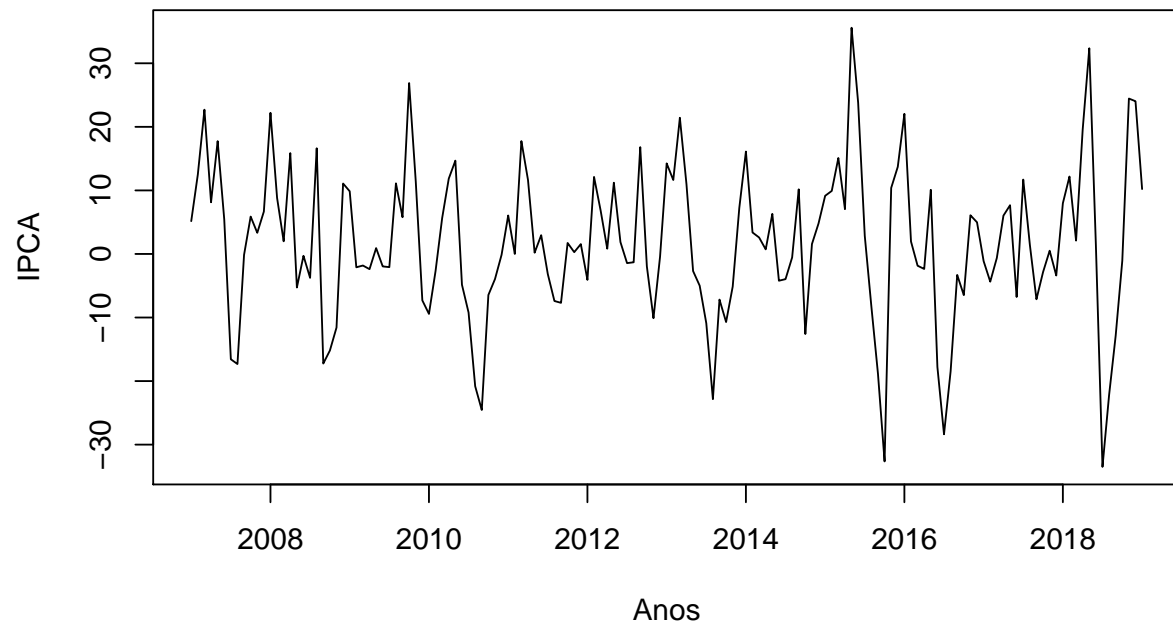
```
plot(zt9,main="Série Temporal do Café", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Café



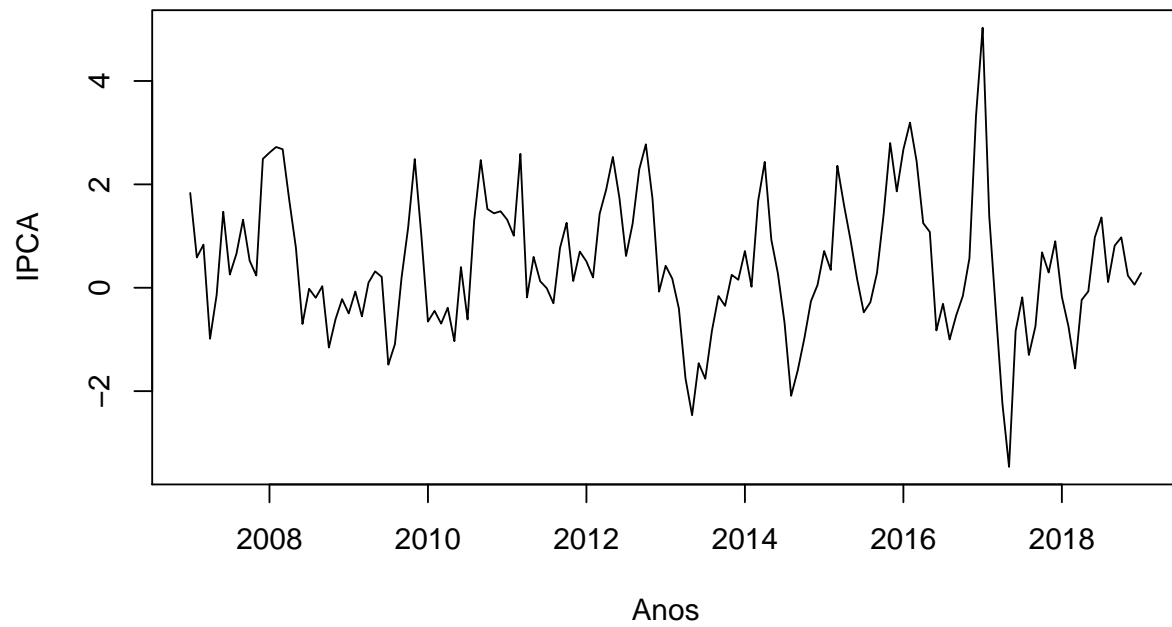
```
plot(zt10,main="Série Temporal da Cebola", xlab= "Anos", ylab="IPCA")
```

Série Temporal da Cebola



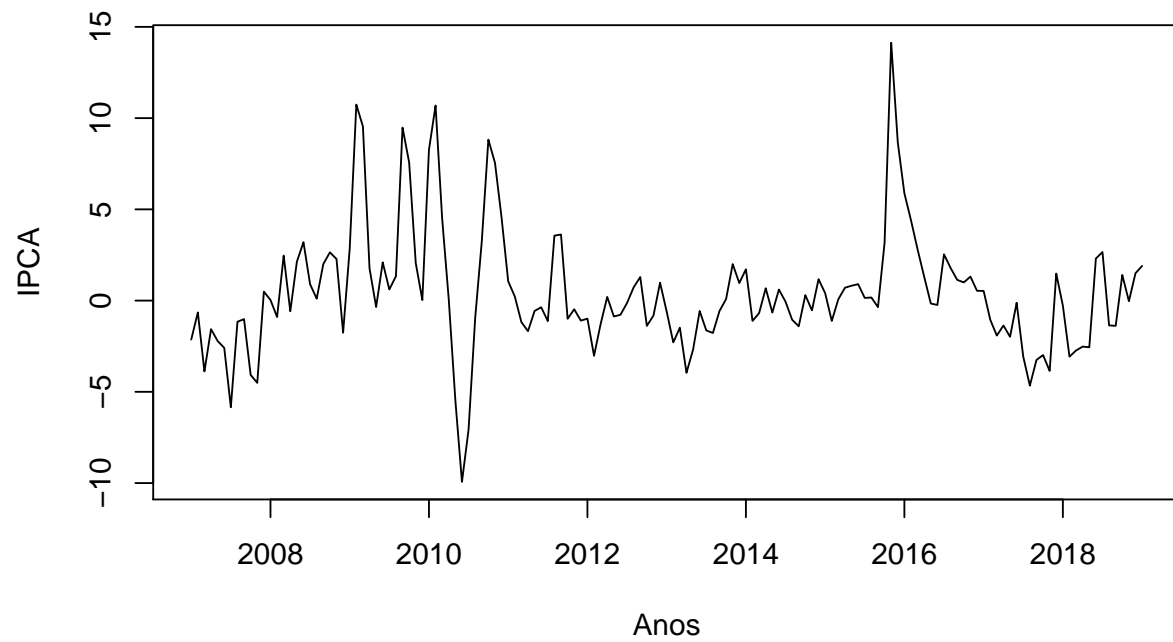
```
plot(zt11,main="Série Temporal do Complexo Soja", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Complexo Soja



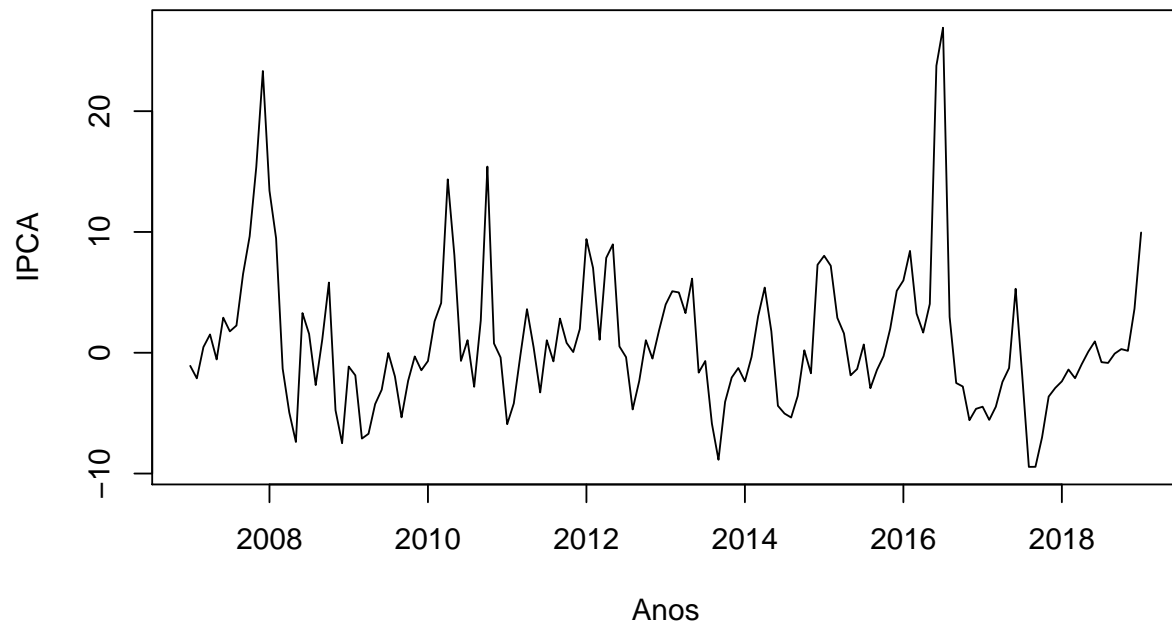
```
plot(zt12,main="Série Temporal do Complexo Sucroalc.", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Complexo Sucoalc.



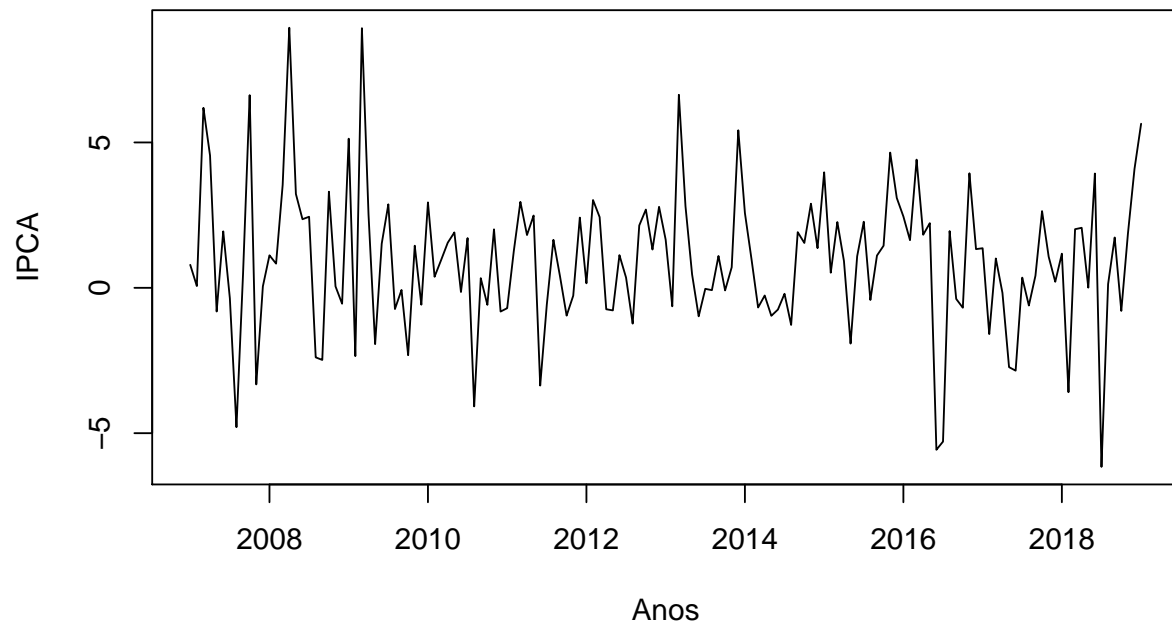
```
#par(mfrow = c(3, 2))  
  
plot(zf13,main="Série Temporal do Feijão", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Feijão



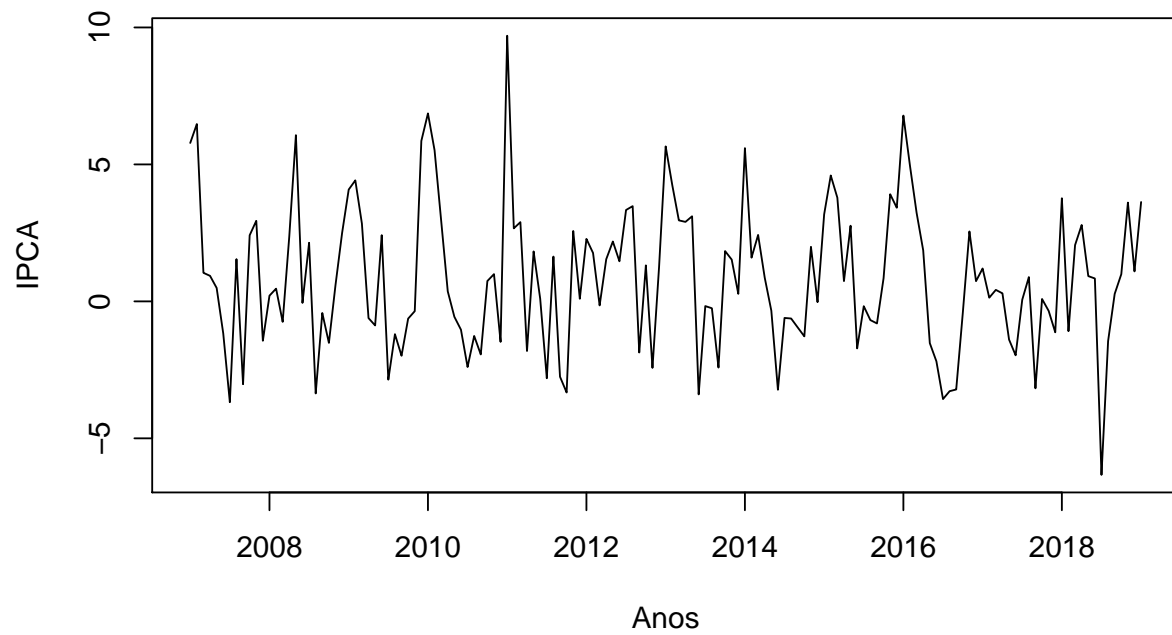
```
plot(zt14,main="Série Temporal das Frutas", xlab= "Anos", ylab="IPCA")
```


Série Temporal das Frutas



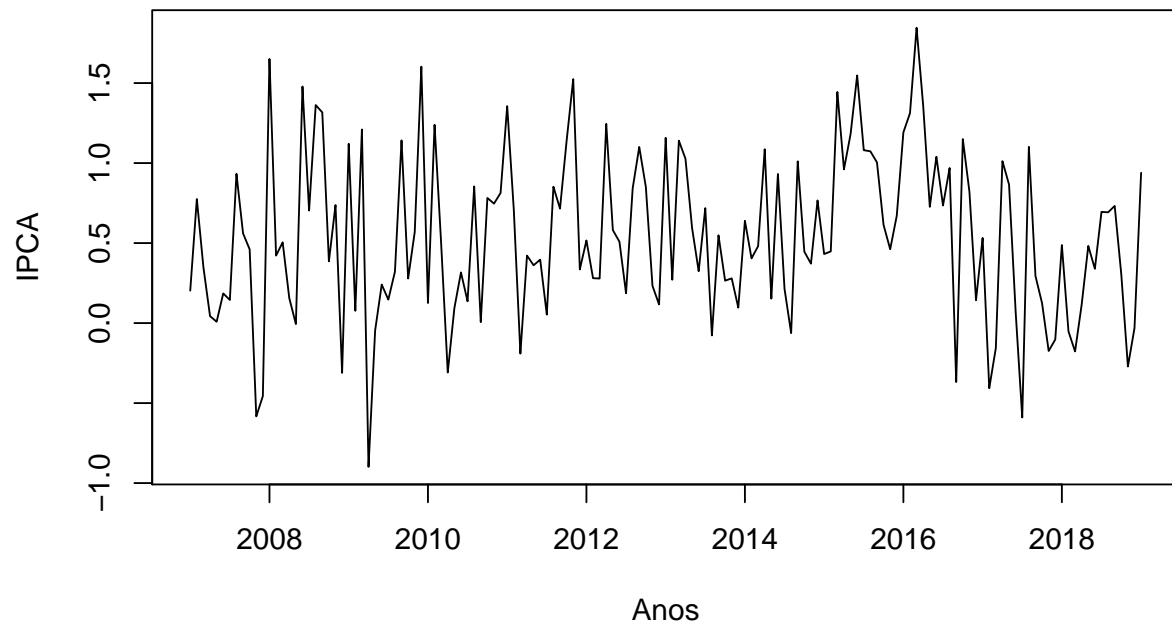
```
plot(zt15,main="Série Temporal das Hortículas", xlab= "Anos", ylab="IPCA")
```

Série Temporal das Hortículas



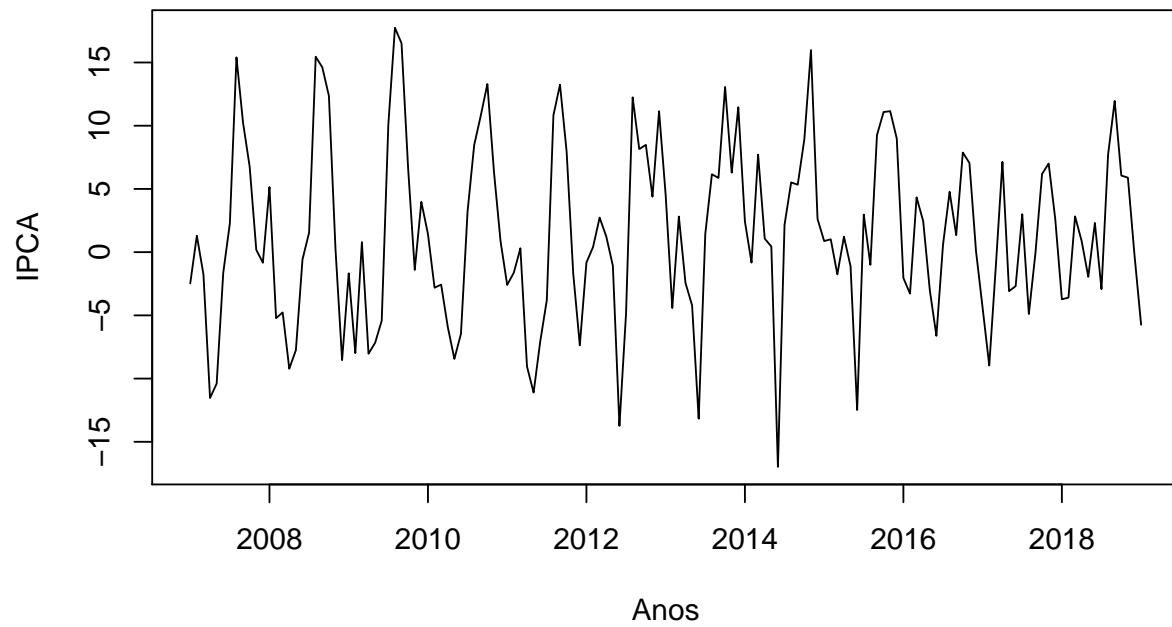
```
plot(zt16,main="Série Temporal de Indefinido", xlab= "Anos", ylab="IPCA")
```

Série Temporal de Indefinido



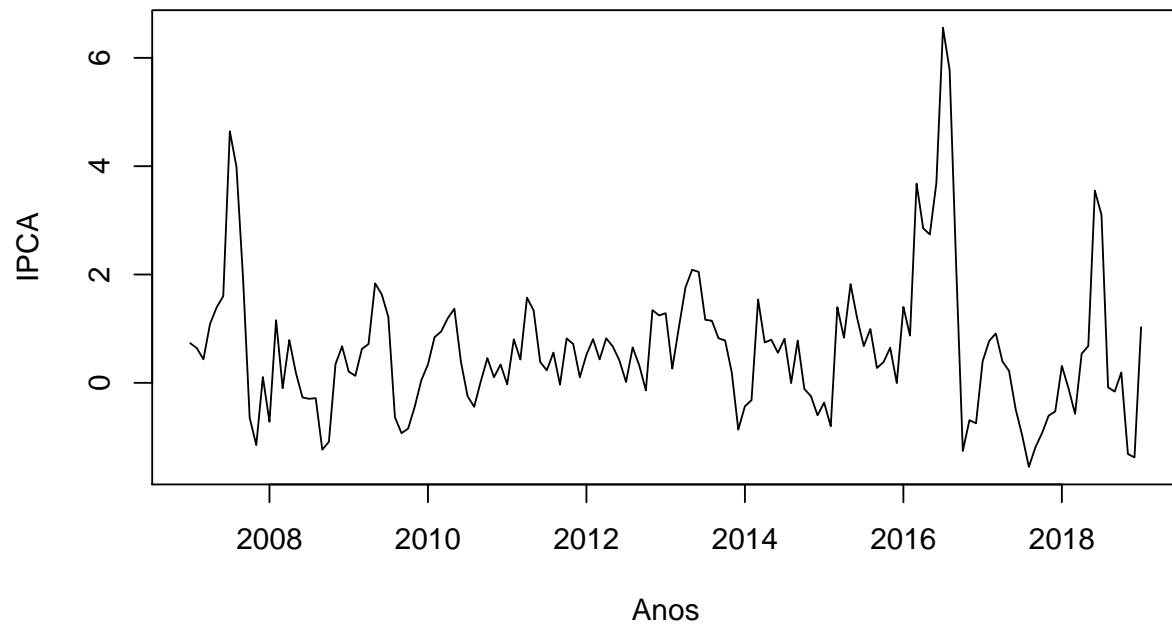
```
plot(zt17,main="Série Temporal do Laranja e Citrus", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Laranja e Citrus



```
plot(zt18,main="Série Temporal da Lácteos", xlab= "Anos", ylab="IPCA")
```

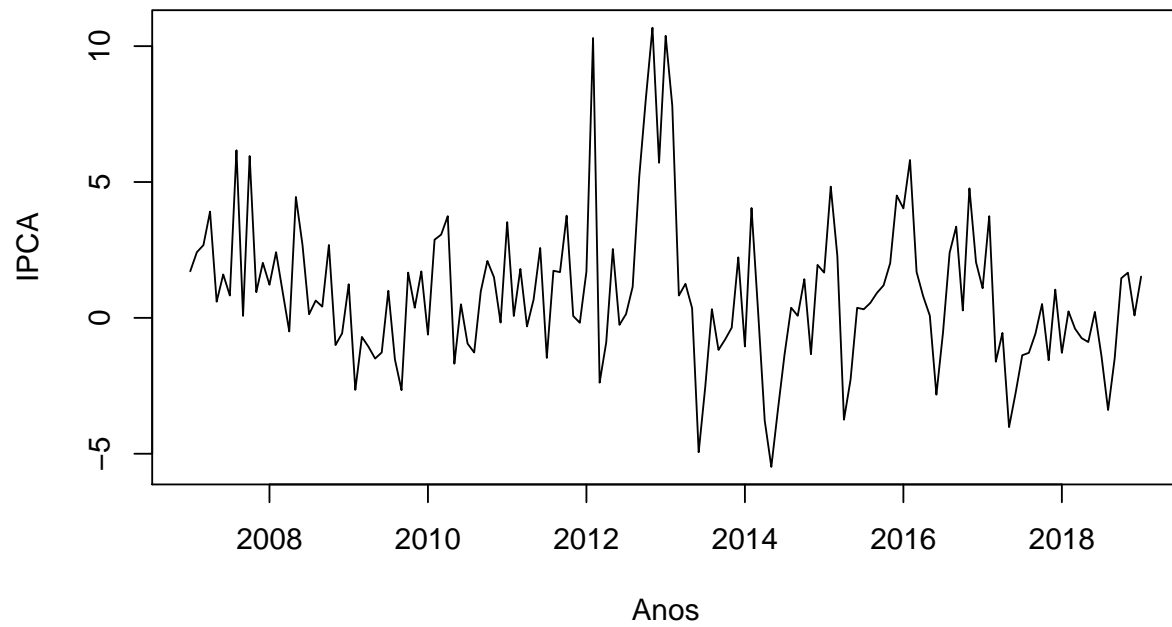
Série Temporal da Lácteos



```
#par(mfrow = c(3, 2))
```

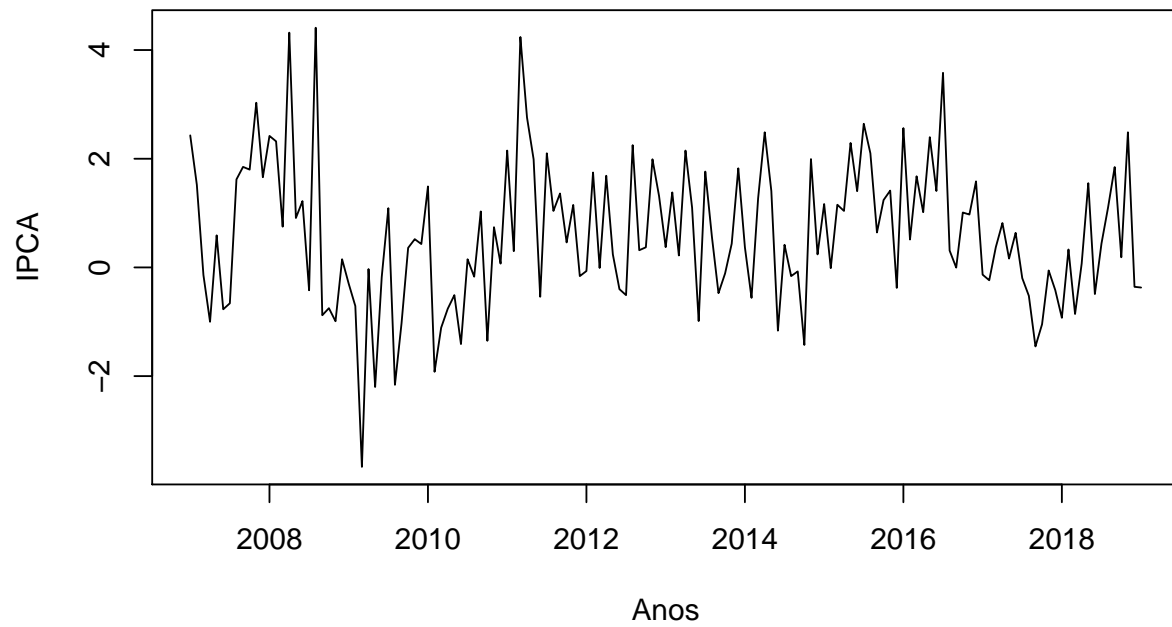
```
plot(zt19,main="Série Temporal da Mandioca", xlab= "Anos", ylab="IPCA")
```

Série Temporal da Mandioca



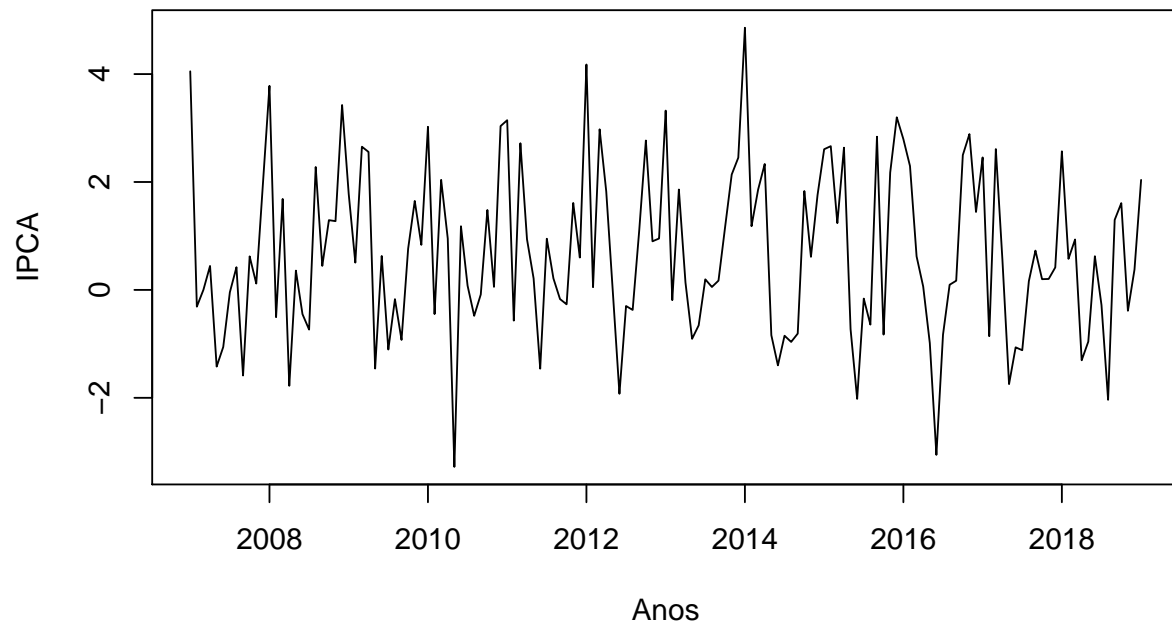
```
plot(zt20,main="Série Temporal do Milho", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Milho



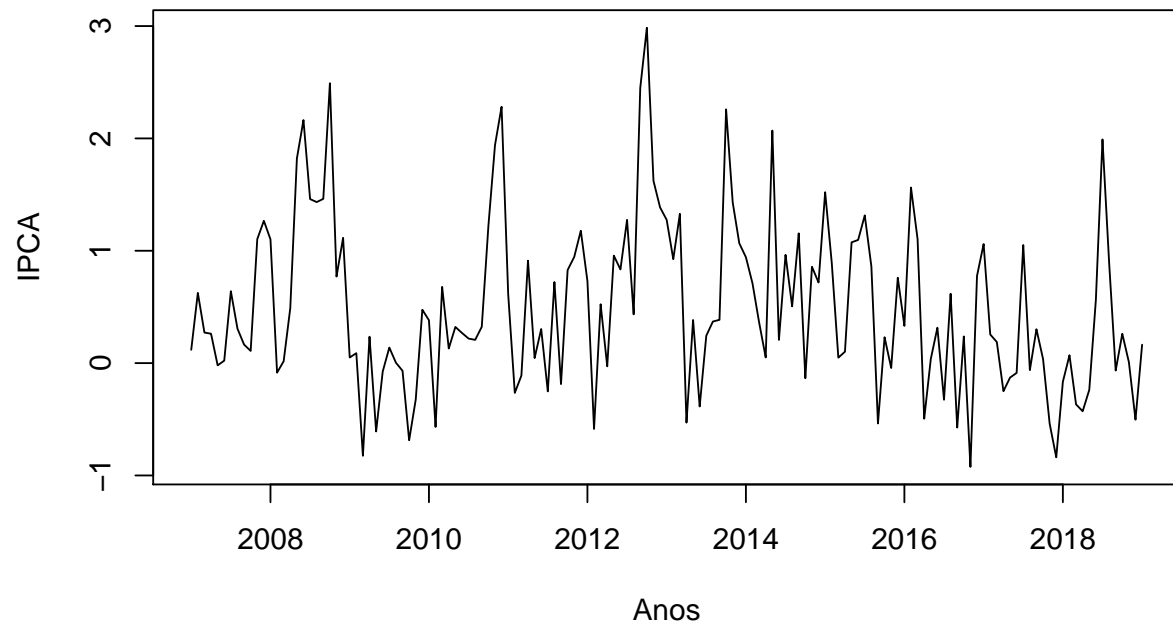
```
plot(zt21,main="Série Temporal do Pescado", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Pescado



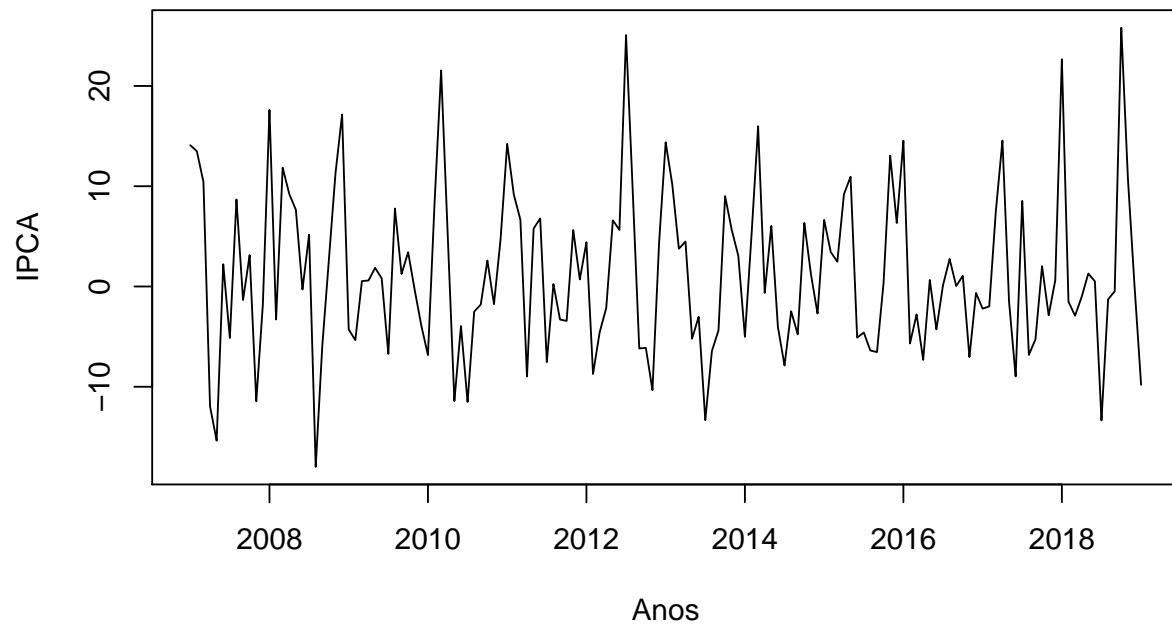
```
plot(zt22,main="Série Temporal da Suínocultura", xlab= "Anos", ylab="IPCA")
```


Série Temporal da Suínocultura



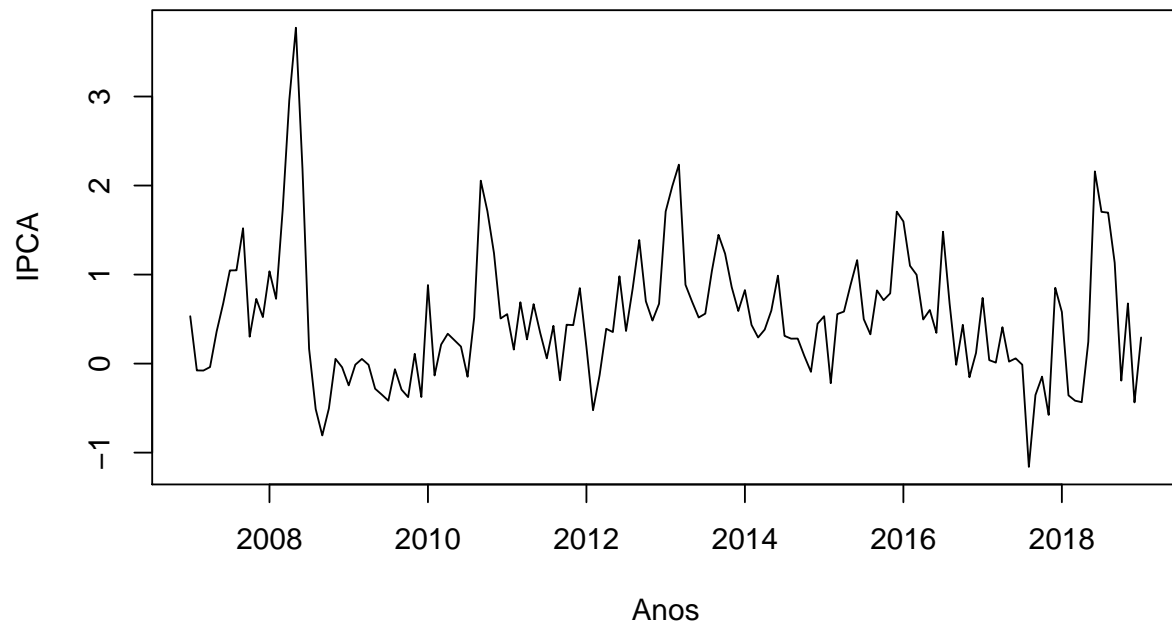
```
plot(zt23,main="Série Temporal do Tomate", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Tomate



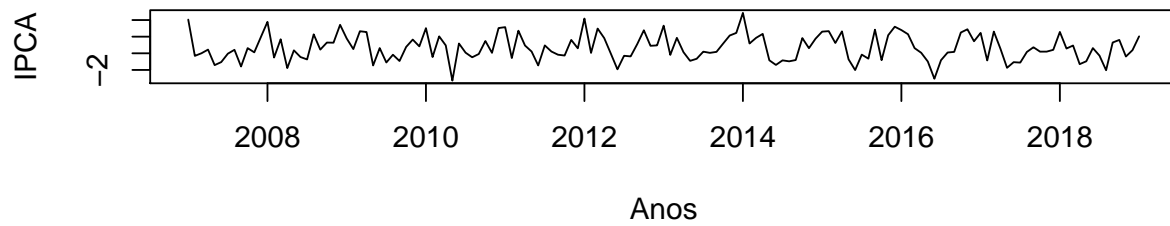
```
plot(zt24,main="Série Temporal do Trigo", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Trigo

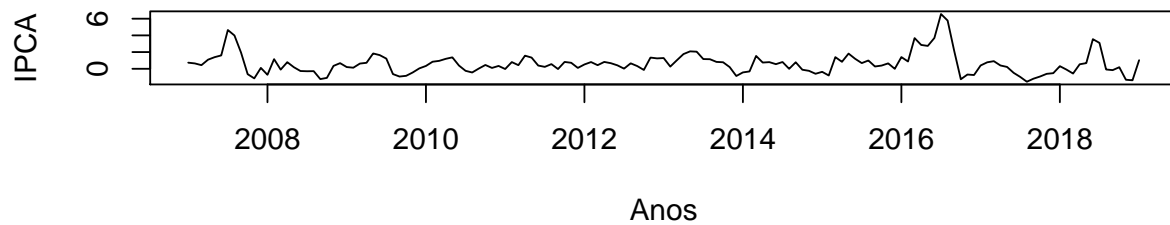


```
par(mfrow = c(2, 1))
plot(zt21,main="Série Temporal do Pescado", xlab= "Anos", ylab="IPCA")
plot(zt18,main="Série Temporal do Lácteos", xlab= "Anos", ylab="IPCA")
```

Série Temporal do Pescado



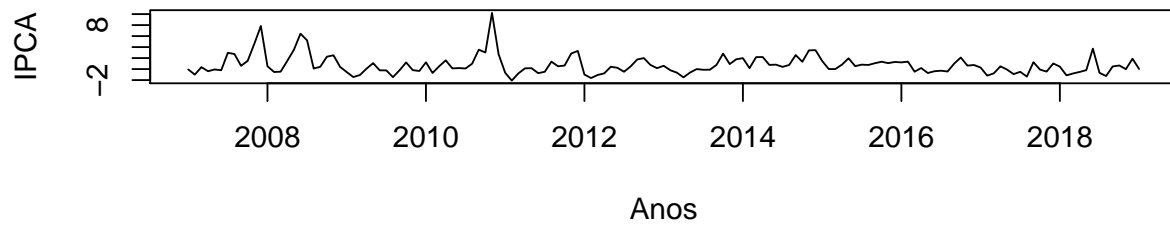
Série Temporal do Lácteos



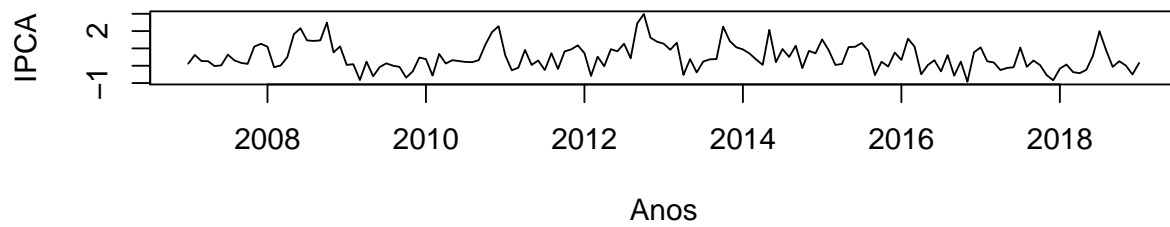
#900#650

```
par(mfrow = c(2, 1))
plot(zt7,main="Série Temporal da Bovinocultura", xlab= "Anos", ylab="IPCA")
plot(zt22,main="Série Temporal da Suínocultura", xlab= "Anos", ylab="IPCA")
```

Série Temporal da Bovinocultura

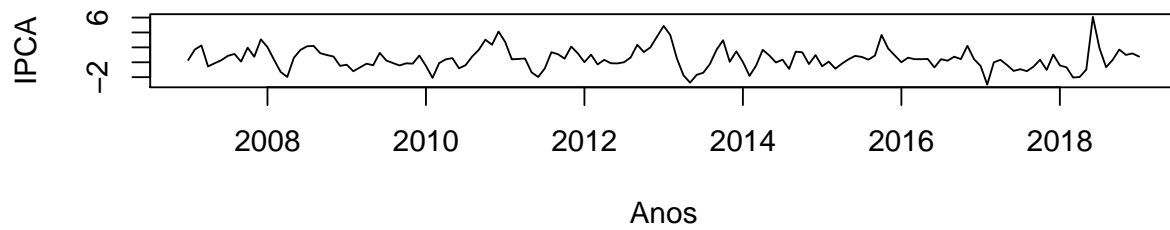


Série Temporal da Suínocultura

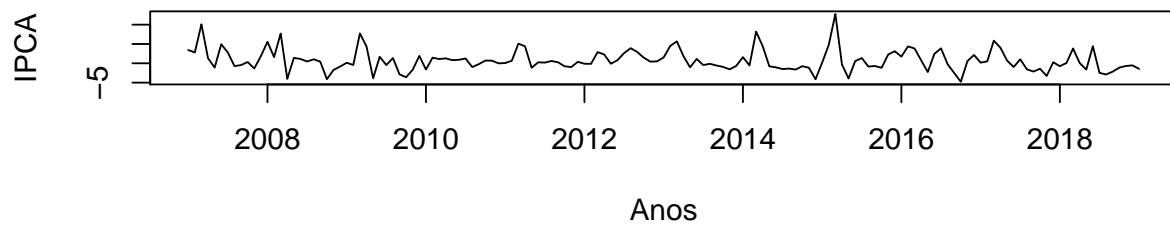


```
par(mfrow = c(2, 1))
plot(zt3,main="Série Temporal de Avicultura de Corte", xlab= "Anos", ylab="IPCA")
plot(zt4,main="Série Temporal de Avicultura de Postura", xlab= "Anos", ylab="IPCA")
```

Série Temporal de Avicultura de Corte



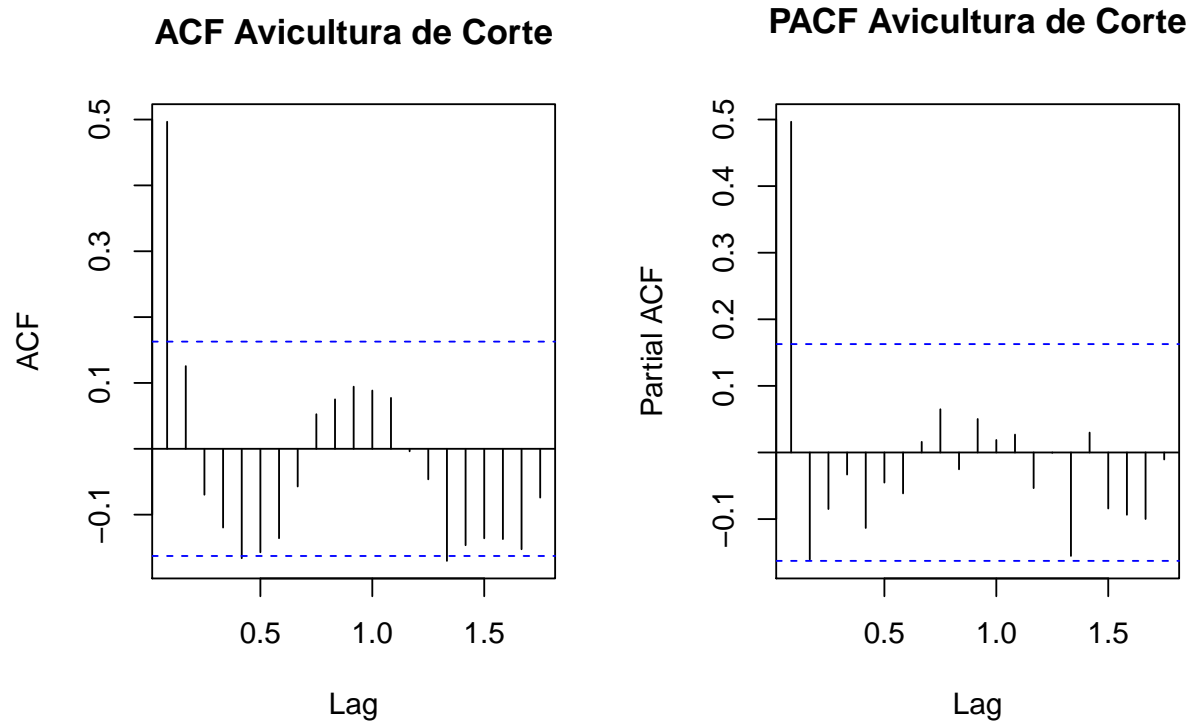
Série Temporal de Avicultura de Postura



Funções de Autocorrelações

Funções de Autocorrelações para Avicultura de Corte

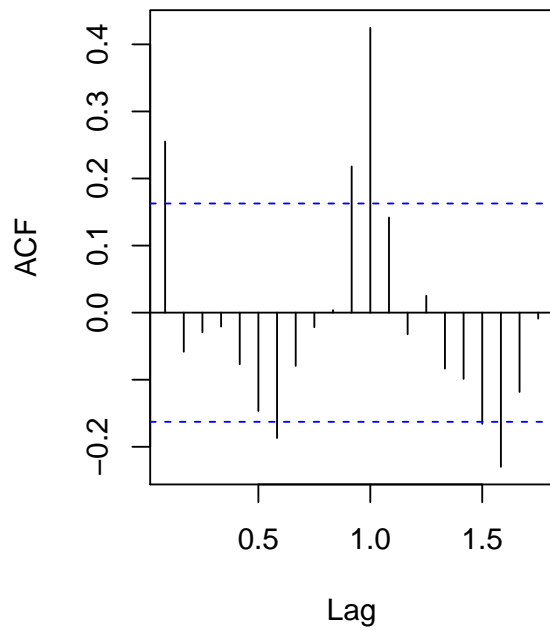
```
#Funções de Autocorrelações para Avicultura de Corte
par(mfrow = c(1, 2))
acf(zt3, main="ACF Avicultura de Corte")
pacf(zt3, main="PACF Avicultura de Corte")
```



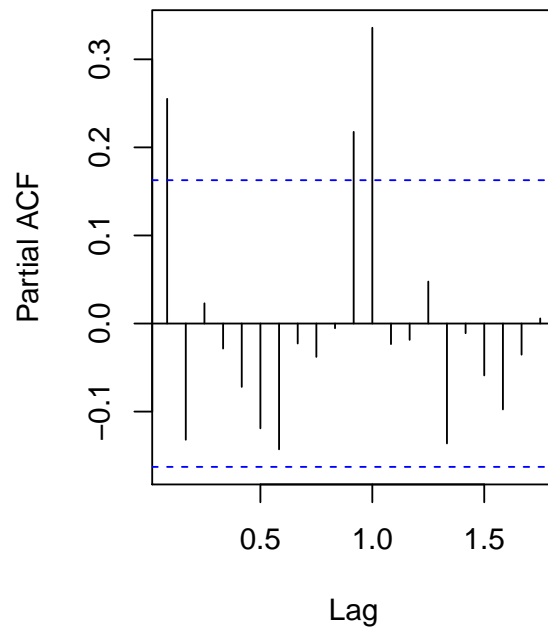
Funções de Autocorrelações para Avicultura de Postura

```
#Funções de Autocorrelações para Avicultura de Postura  
par(mfrow = c(1, 2))  
acf(zt4, main="ACF Avicultura de Postura")  
pacf(zt4, main="PACF Avicultura de Postura")
```

ACF Avicultura de Postura

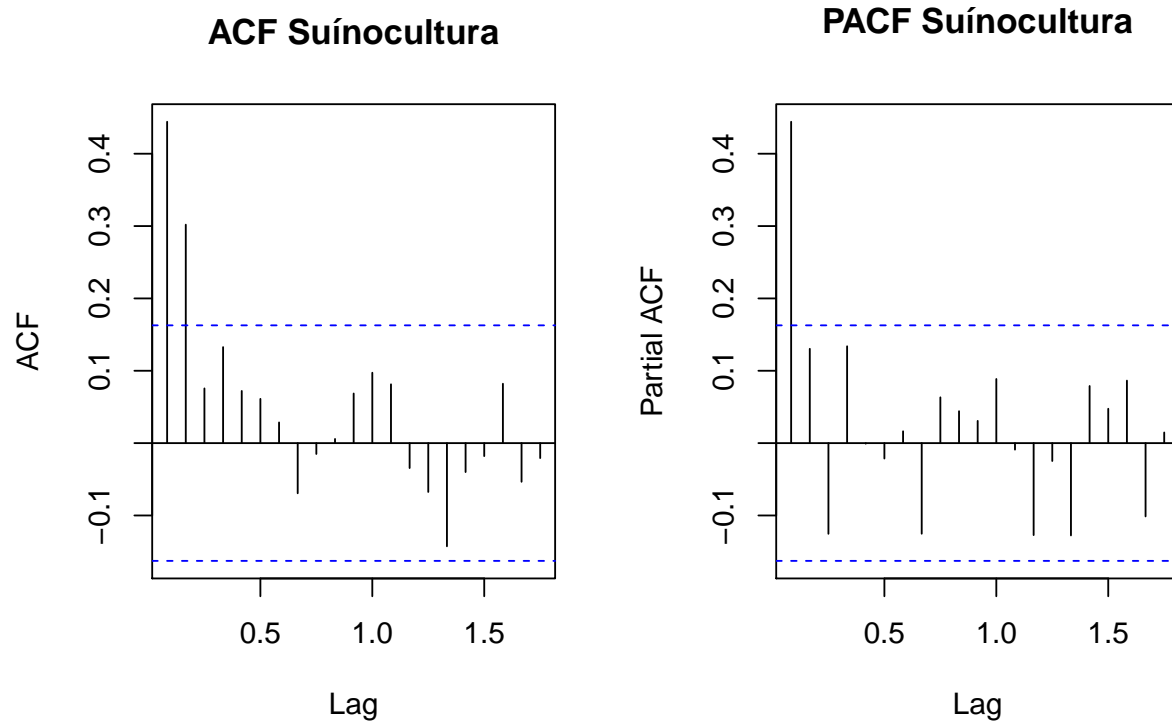


PACF Avicultura de Postura



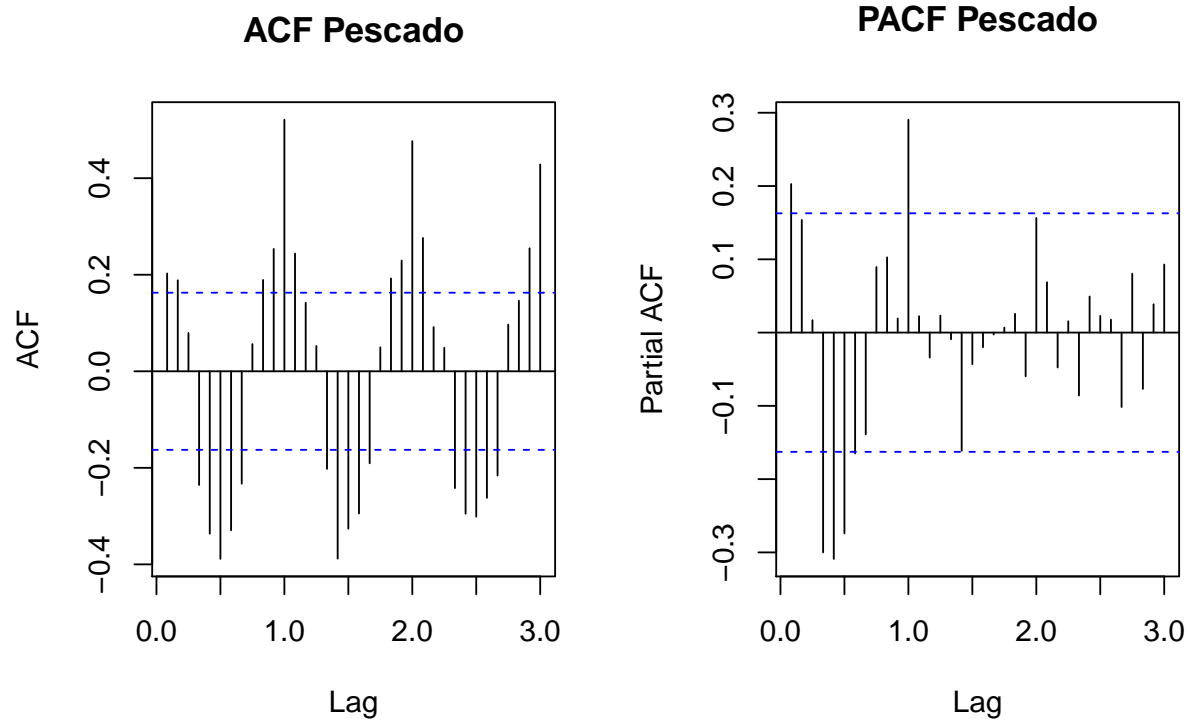
Funções de Autocorrelações para Suinocultura

```
#Funções de Autocorrelações para Suinocultura  
par(mfrow = c(1, 2))  
acf(zt22, main="ACF Suínocultura")  
pacf(zt22, main="PACF Suínocultura")
```

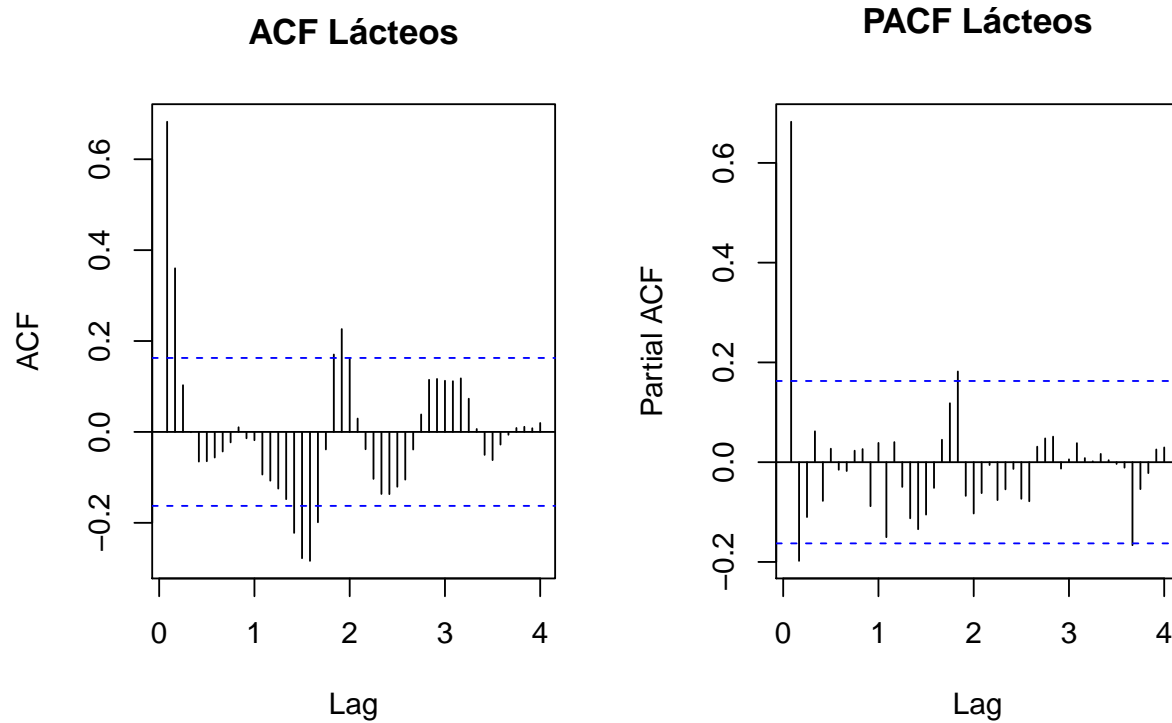
Funções de Autocorrelações para Pescado

```
#Funções de Autocorrelações para Pescado
par(mfrow = c(1, 2))
acf(zt21, main="ACF Pescado", lag.max = 36)
pacf(zt21, main="PACF Pescado", lag.max = 36)
```



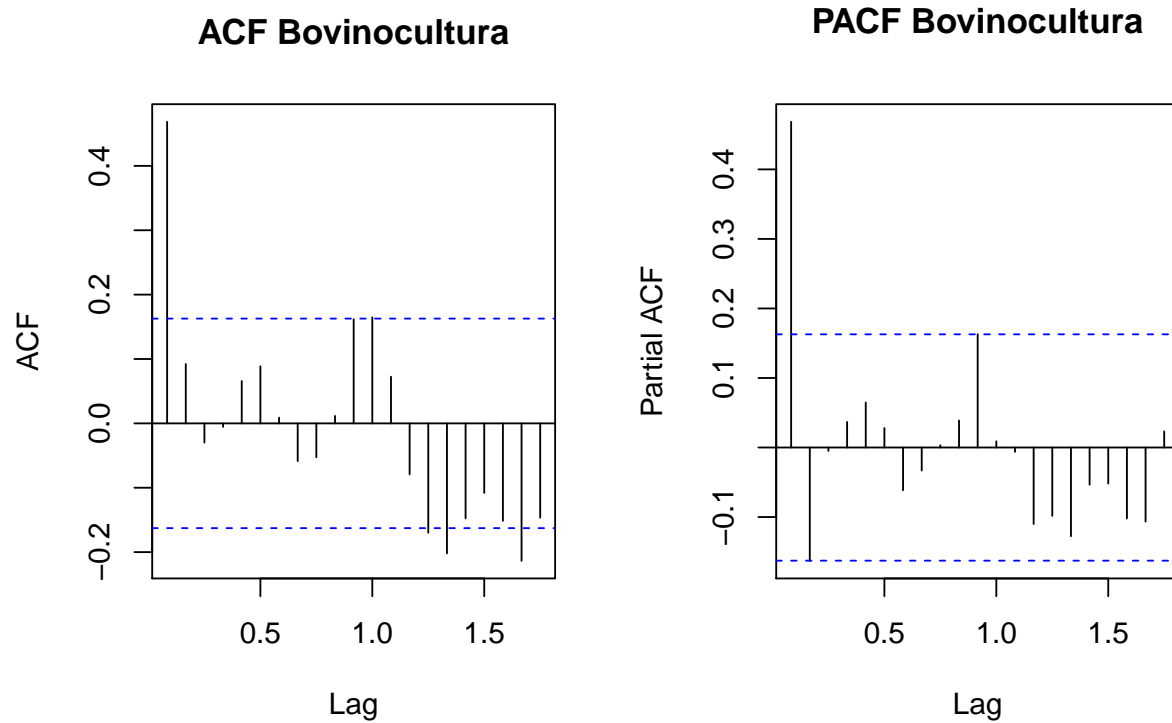
Funções de Autocorrelações para Lácteos

```
#Funções de Autocorrelações para Lácteos
par(mfrow = c(1, 2))
acf(zt18, main="ACF Lácteos", lag.max = 48)
pacf(zt18, main="PACF Lácteos", lag.max = 48)
```



Funções de Autocorrelações para Bovinocultura

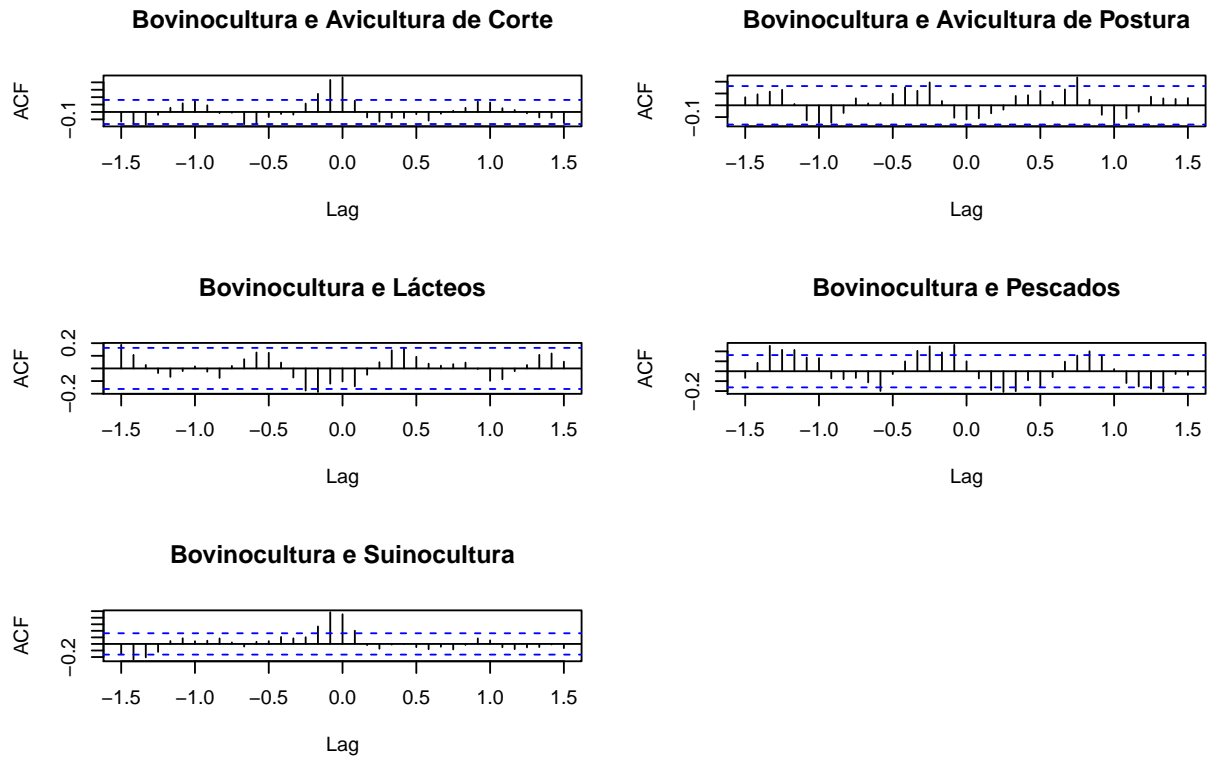
```
#Funções de Autocorrelações para Bovinocultura
par(mfrow = c(1, 2))
acf(zt7, main="ACF Bovinocultura")
pacf(zt7, main="PACF Bovinocultura")
```



Análise Correlação Cruzada

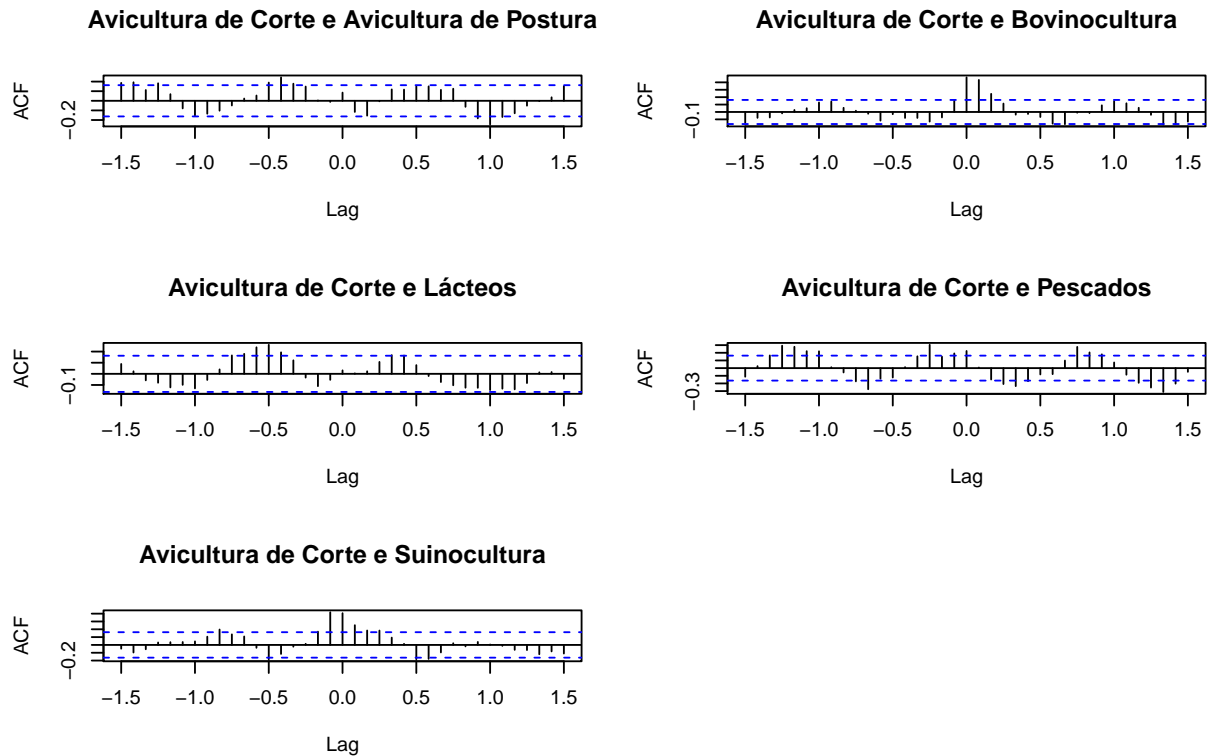
Correlações cruzadas da Bovinocultura

```
#Correlações cruzadas da Bovinocultura
par(mfrow = c(3,2))
ccf(zt7,zt3,main="Bovinocultura e Avicultura de Corte")
ccf(zt7,zt4,main="Bovinocultura e Avicultura de Postura")
ccf(zt7,zt18,main="Bovinocultura e Lâcteos")
ccf(zt7,zt21,main="Bovinocultura e Pescados")
ccf(zt7,zt22,main="Bovinocultura e Suinocultura")
```



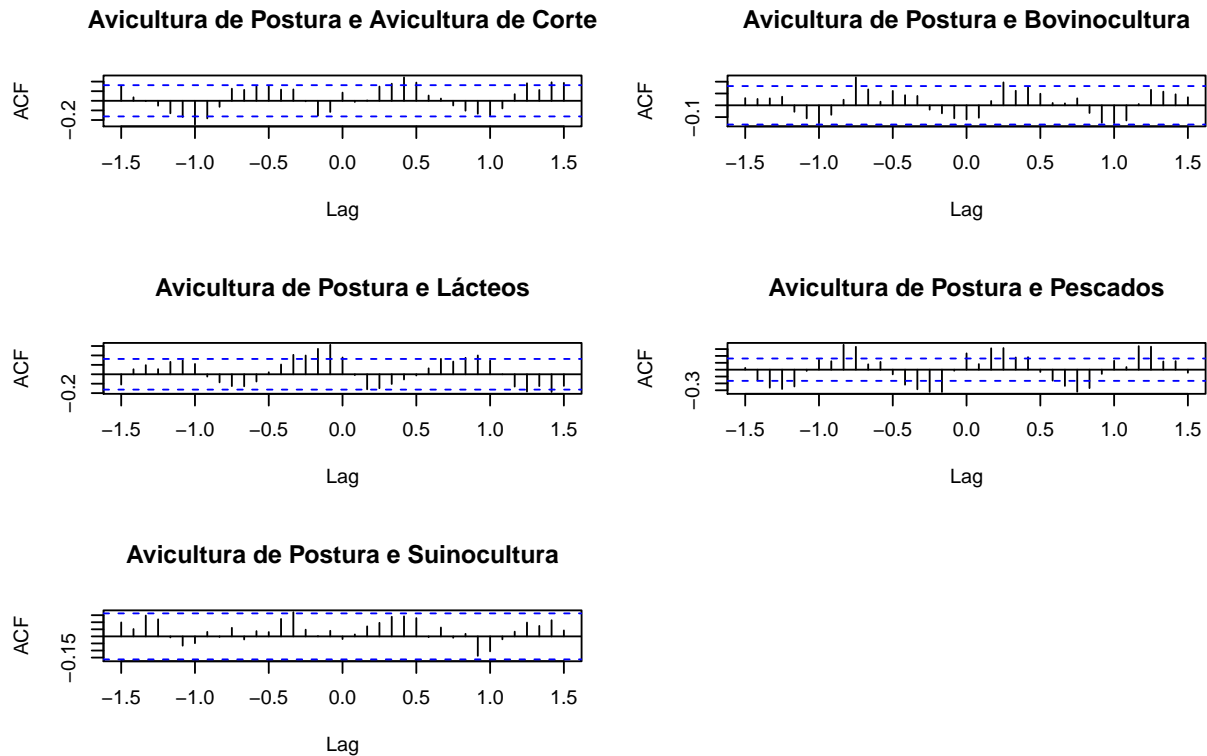
Correlações cruzadas da Avicultura de Corte

```
#Correlações cruzadas da Avicultura de Corte
par(mfrow = c(3,2))
ccf(zt3,zt4,main="Avicultura de Corte e Avicultura de Postura")
ccf(zt3,zt7,main="Avicultura de Corte e Bovinocultura")
ccf(zt3,zt18,main="Avicultura de Corte e Lácteos")
ccf(zt3,zt21,main="Avicultura de Corte e Pescados")
ccf(zt3,zt22,main="Avicultura de Corte e Suinocultura")
```



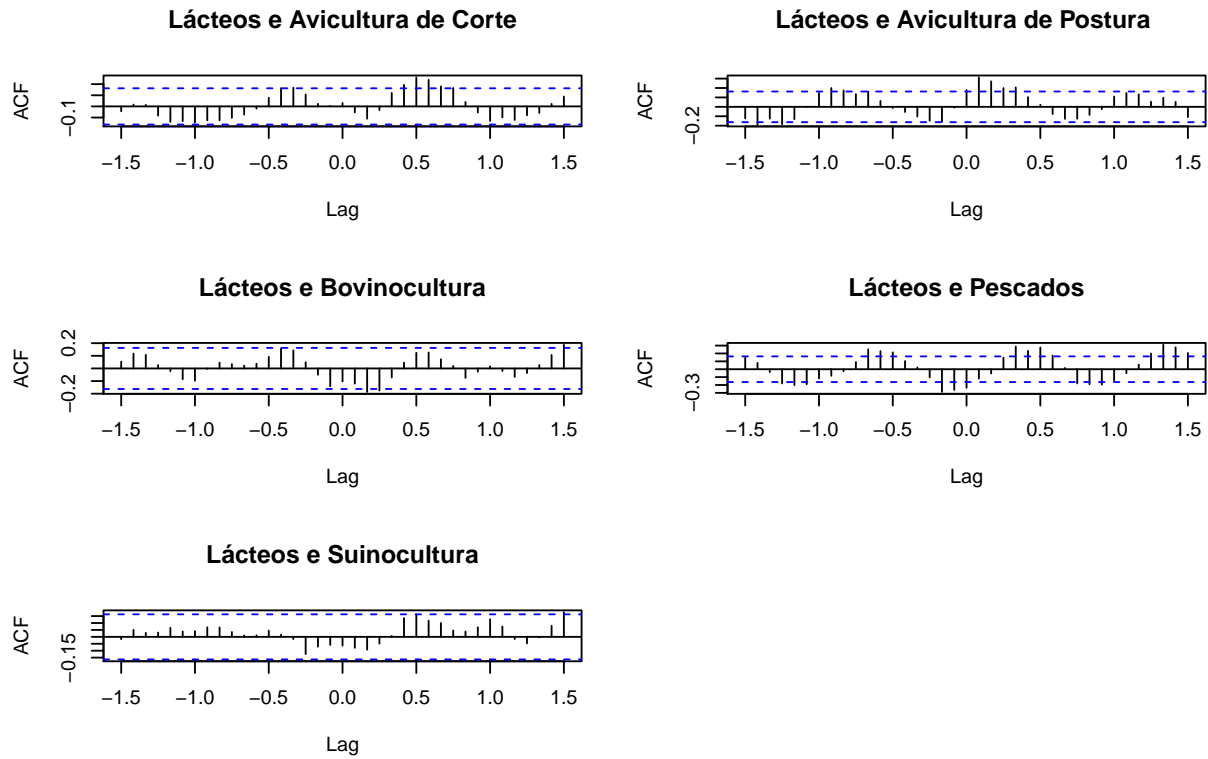
Correlações cruzadas da Avicultura de Postura

```
#Correlações cruzadas da Avicultura de Postura
par(mfrow = c(3,2))
ccf(zt4,zt3,main="Avicultura de Postura e Avicultura de Corte")
ccf(zt4,zt7,main="Avicultura de Postura e Bovinocultura")
ccf(zt4,zt18,main="Avicultura de Postura e Lácteos")
ccf(zt4,zt21,main="Avicultura de Postura e Pescados")
ccf(zt4,zt22,main="Avicultura de Postura e Suinocultura")
```



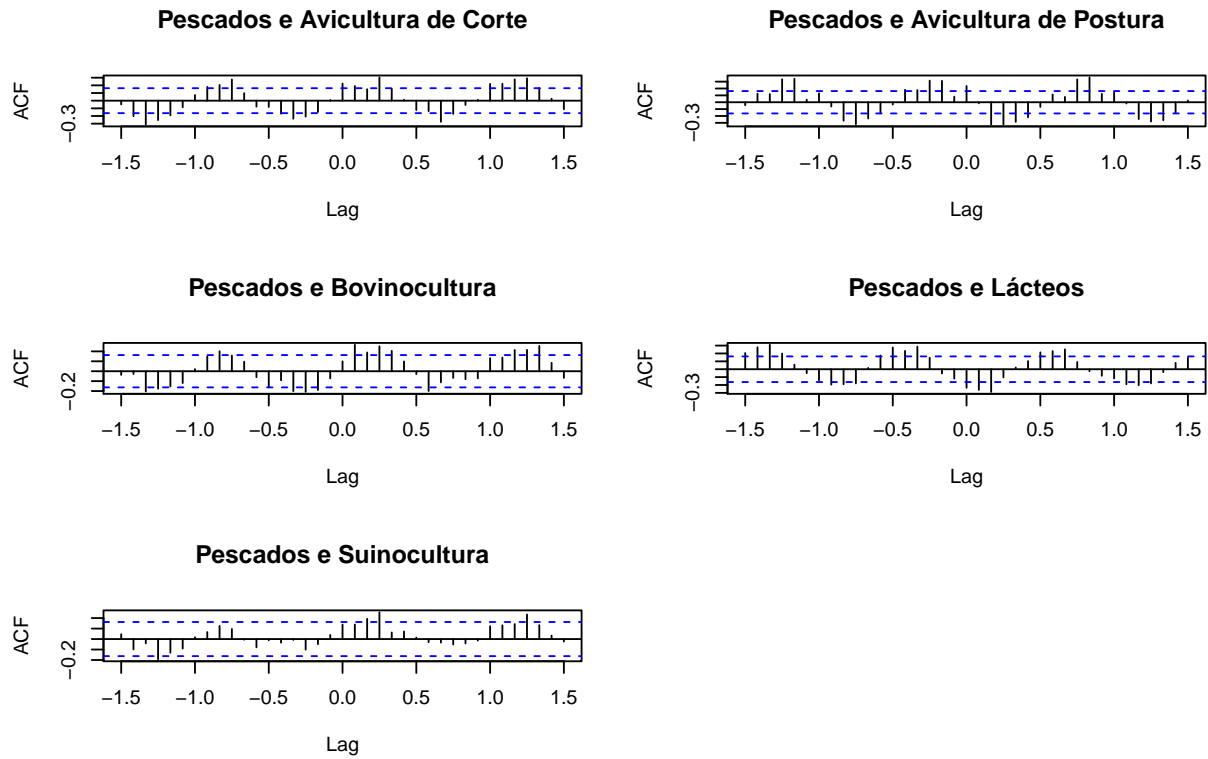
Correlações cruzadas dos Lácteos

```
#Correlações cruzadas dos Lácteos
par(mfrow = c(3,2))
ccf(zt18,zt3,main="Lácteos e Avicultura de Corte")
ccf(zt18,zt4,main="Lácteos e Avicultura de Postura ")
ccf(zt18,zt7,main="Lácteos e Bovinocultura")
ccf(zt18,zt21,main="Lácteos e Pescados")
ccf(zt18,zt22,main="Lácteos e Suinocultura")
```



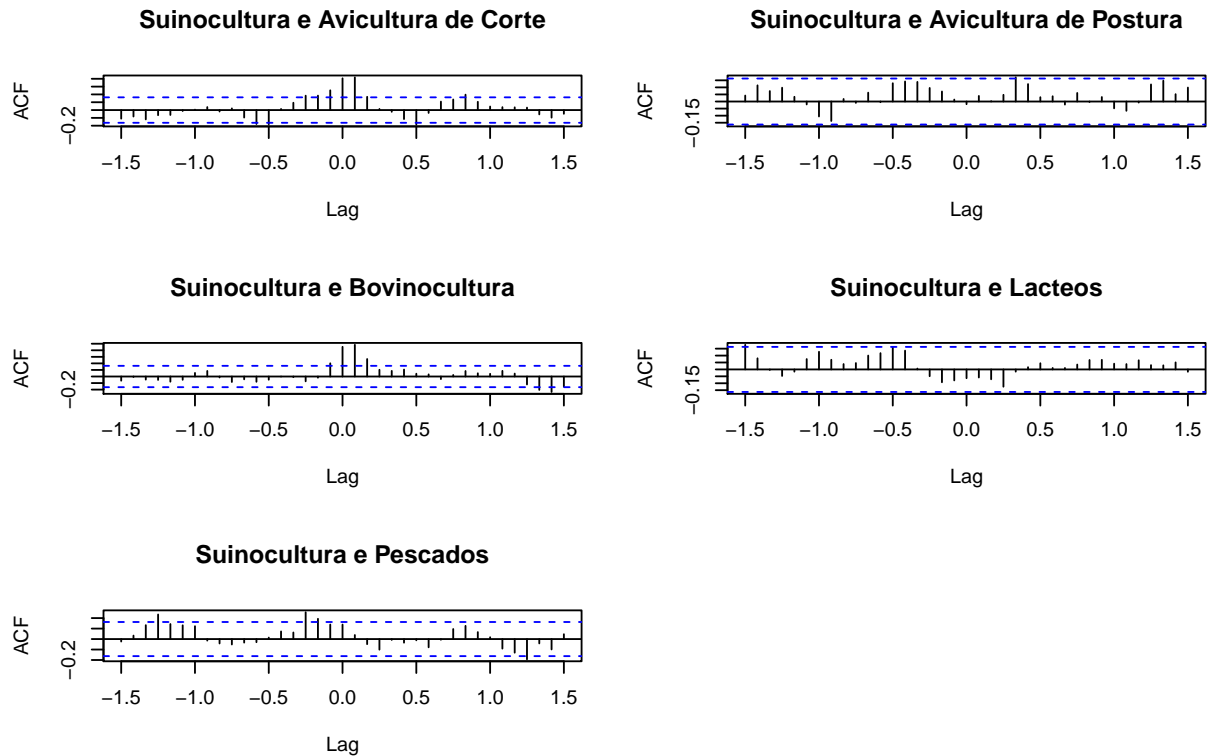
Correlações cruzadas dos Pescados

```
# Correlações cruzadas dos Pescados
par(mfrow = c(3,2))
ccf(zt21,zt3,main="Pescados e Avicultura de Corte")
ccf(zt21,zt4,main="Pescados e Avicultura de Postura")
ccf(zt21,zt7,main="Pescados e Bovinocultura")
ccf(zt21,zt18,main="Pescados e Lácteos")
ccf(zt21,zt22,main="Pescados e Suinocultura")
```

Correlações cruzadas da Suinocultura

```
#Correlações cruzadas da Suinocultura
par(mfrow = c(3,2))
ccf(zt22,zt3,main="Suinocultura e Avicultura de Corte")
ccf(zt22,zt4,main="Suinocultura e Avicultura de Postura")
ccf(zt22,zt7,main="Suinocultura e Bovinocultura")
ccf(zt22,zt18,main="Suinocultura e Lacteos")
ccf(zt22,zt21,main="Suinocultura e Pescados")
```



Selecionado as variáveis de interesse do estudo

Essa função retorna a coluna com a lag a ser considerada na análise

#Essa função retorna a coluna com a lag a ser considerada na análise

```
funcao_lags = function(df,coluna,nome,lag){
  n = nrow(df)
  pre = rep(NA,lag)
  newcol = c(pre,coluna)
  for (k in 1:lag){
    df = rbind(df,rep(NA,ncol(df)))
  }
  df[nome] = newcol
  return (df)
}
```

A função a baixo retira as variáveis do modelo em função do p-valor

#A função a baixo retira as variáveis do modelo em função do p-valor

```
tirar_variaveis = function(p,d,q,x,y){
  v = p + q + 1
  max = 0.06
  while (max > 0.05){
    model = Arima(y,order=c(p,d,q),xreg = x)
    ct = coeftest(model)
```

```

pvalues = ct[(v+1):nrow(ct),4]
maxi = which.max(pvalues)
max = ct[v + maxi,4]
if (max > 0.05) {
  x = x[,-maxi]
}
}
lista = list(ct, x)
return (lista)
}

```

A seguir vamos selecionar apenas as variáveis de interesse para análise

```

#A seguir vamos selecionar apenas as variáveis de interesse para análise
data_cut = data[,c("Bovinocultura", "Avicultura de Corte", "Avicultura de Postura", "Pescado", "Lácteos", "S

```

Modelo da Bovinocultura

Estruturando a base

```

#Estruturando a base
df1<- funcao_lags(data_cut, data_cut$'Avicultura de Postura', 'avp9', 9)
df1 <- funcao_lags(df1, df1$Pescado, 'p3', 3)
df1 <- funcao_lags(df1, df1$Pescado, 'p10', 10)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'b1', 1)

df2 <- na.omit(df1)

```

Separando variável preditora e as covariáveis

```

#Separando variável preditora e as covariáveis
x = model.matrix(Bovinocultura~.,df2)[,-1]
y = df2$Bovinocultura

```

Regressão classifica no contexto de Séries Temporais

Criando o modelo de Regressão Simples

```

#Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

```

```

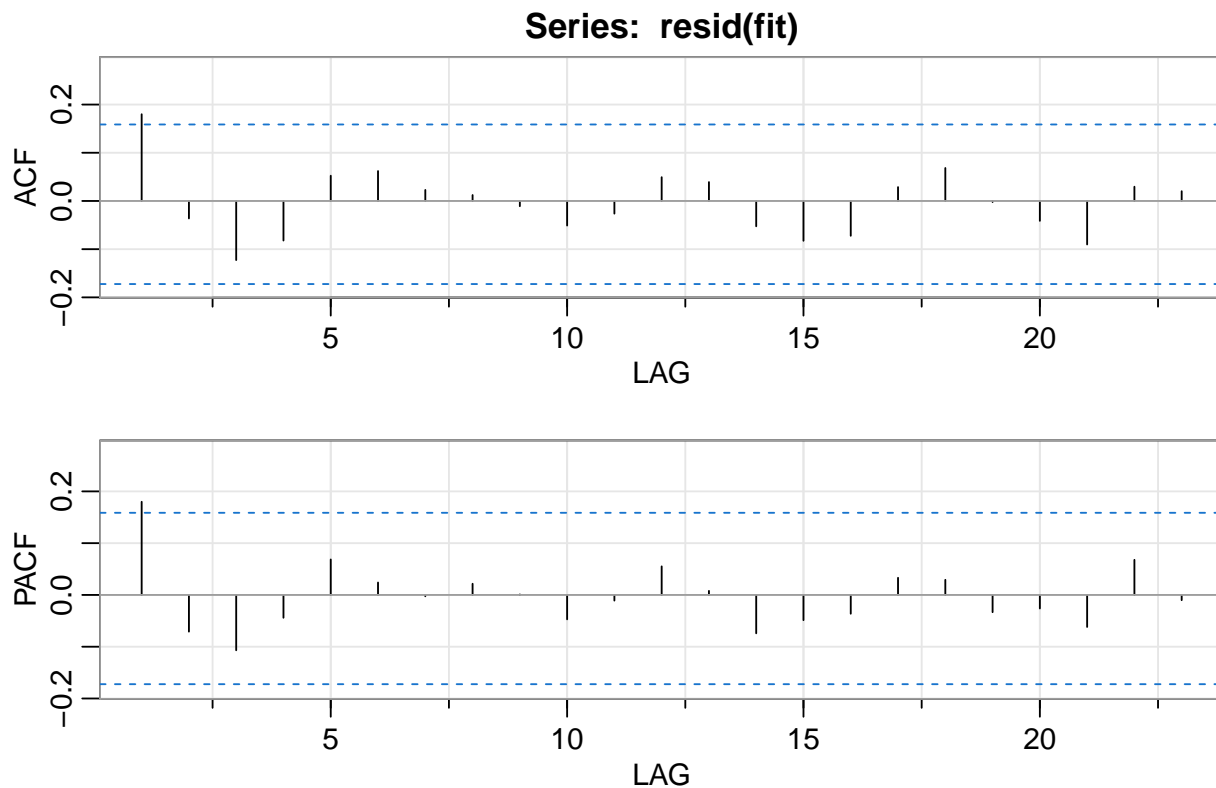
##
## Call:
## lm(formula = y ~ x)
##
## Residuals:

```

```
##      Min      1Q  Median      3Q      Max
## -3.5314 -0.9189 -0.0157  0.5586  8.5757
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.28536    0.20364   1.401 0.163405
## x'Avicultura de Corte'  0.41328    0.11349   3.642 0.000384 ***
## x'Avicultura de Postura' 0.04542    0.06035   0.753 0.452982
## xPescado          -0.26037    0.11194  -2.326 0.021498 *
## xLácteos          -0.20785    0.12322  -1.687 0.093939 .
## xSuinocultura      0.28048    0.21162   1.325 0.187266
## xavp9              0.17980    0.05358   3.356 0.001026 **
## xp3                -0.02202    0.10186  -0.216 0.829147
## xp10               0.07166    0.10163   0.705 0.481954
## xbl                 0.37950    0.09758   3.889 0.000157 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.636 on 136 degrees of freedom
## Multiple R-squared:  0.4224, Adjusted R-squared:  0.3841
## F-statistic: 11.05 on 9 and 136 DF, p-value: 8.134e-13
```

Análise dos Resíduos

```
#Análise dos Resíduos
acf2(resid(fit))
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.18 -0.04 -0.12 -0.08 0.05 0.06 0.02 0.01 -0.01 -0.05 -0.03 0.05 0.04
## PACF 0.18 -0.07 -0.11 -0.04 0.07 0.02 0.00 0.02 0.00 -0.05 -0.01 0.06 0.01
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF  -0.05 -0.08 -0.07 0.03 0.07 0.00 -0.04 -0.09 0.03 0.02
## PACF -0.07 -0.05 -0.04 0.03 0.03 -0.03 -0.03 -0.06 0.07 -0.01
```

Regressão com erros autocorrelacionais

Análise dos resíduos e seleção de variáveis de acordo com p-valor

#Análise dos resíduos e seleção de variáveis de acordo com p-valor

```
fit2 <- tirar_variaveis(0, 0, 0, x, y)
fit2[[1]]
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## intercept          0.288306   0.153111  1.8830 0.0597017 .
## 'Avicultura de Corte' 0.442471   0.105529  4.1929 2.754e-05 ***
## Pescado             -0.200620   0.097816 -2.0510 0.0402669 *
## avp9                 0.179147   0.052350  3.4221 0.0006214 ***
## b1                   0.442780   0.088166  5.0221 5.110e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
xx <- fit2[2]
xx<- xx[[1]]

fit3 = Arima(y,order=c(0,0,0),xreg=xx)
fit3
```

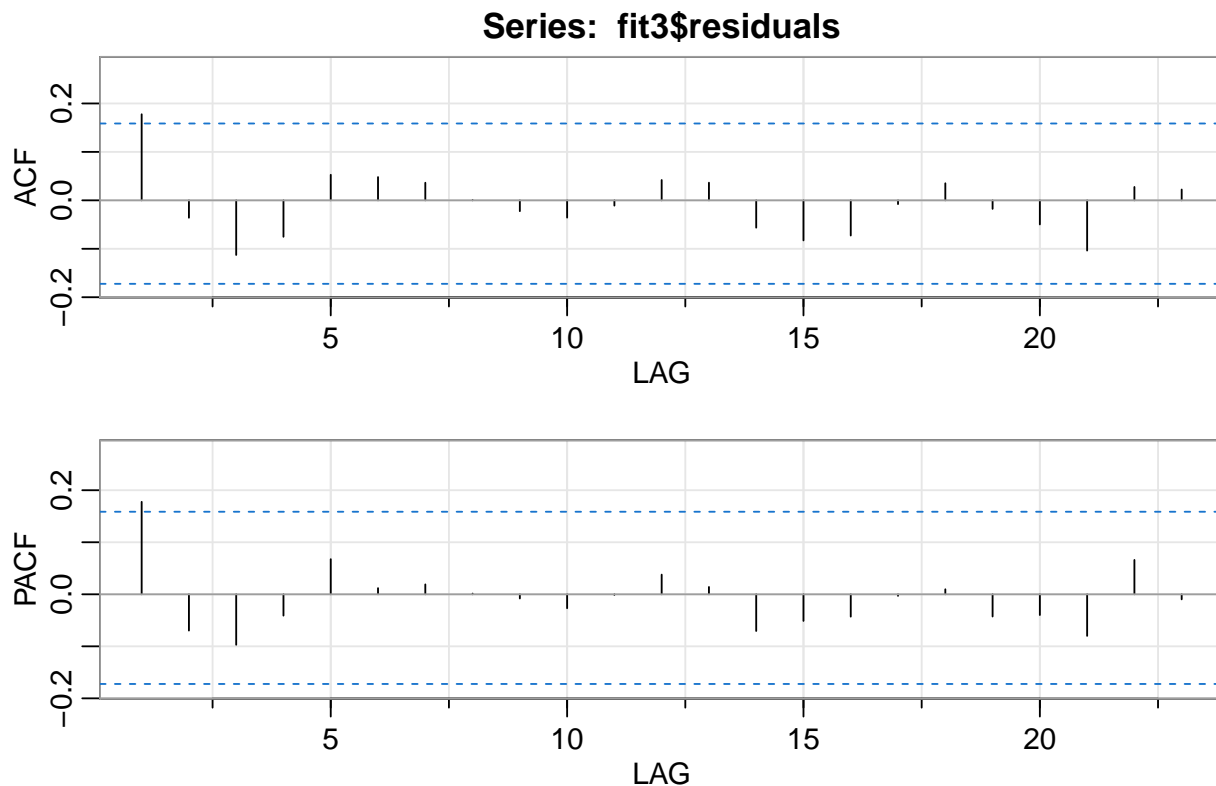
```
## Series: y
## Regression with ARIMA(0,0,0) errors
##
## Coefficients:
##      intercept  'Avicultura de Corte'  Pescado    avp9      b1
##           0.2883                0.4425 -0.2006  0.1791  0.4428
## s.e.        0.1531                0.1055   0.0978  0.0523  0.0882
##
## sigma^2 estimated as 2.693:  log likelihood=-276.95
## AIC=565.9   AICc=566.51   BIC=583.81
```

```
coeftest(fit3)
```

```
##
## z test of coefficients:
##
```

```
##               Estimate Std. Error z value Pr(>|z|)
## intercept      0.288306   0.153111  1.8830 0.0597017 .
## 'Avicultura de Corte' 0.442471   0.105529  4.1929 2.754e-05 ***
## Pescado        -0.200620   0.097816 -2.0510 0.0402669 *
## avp9           0.179147   0.052350  3.4221 0.0006214 ***
## b1             0.442780   0.088166  5.0221 5.110e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
acf2(fit3$residuals)
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.18 -0.04 -0.11 -0.08 0.05 0.05 0.04  0 -0.02 -0.04 -0.01  0.04  0.04
## PACF 0.18 -0.07 -0.10 -0.04 0.07 0.01 0.02  0 -0.01 -0.03  0.00  0.04  0.01
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF  -0.06 -0.08 -0.07 -0.01  0.04 -0.02 -0.05 -0.10  0.03  0.02
## PACF -0.07 -0.05 -0.04  0.00  0.01 -0.04 -0.04 -0.08  0.07 -0.01
```

```
fit4 = Arima(y,order=c(1,0,0),xreg=xx)
fit4
```

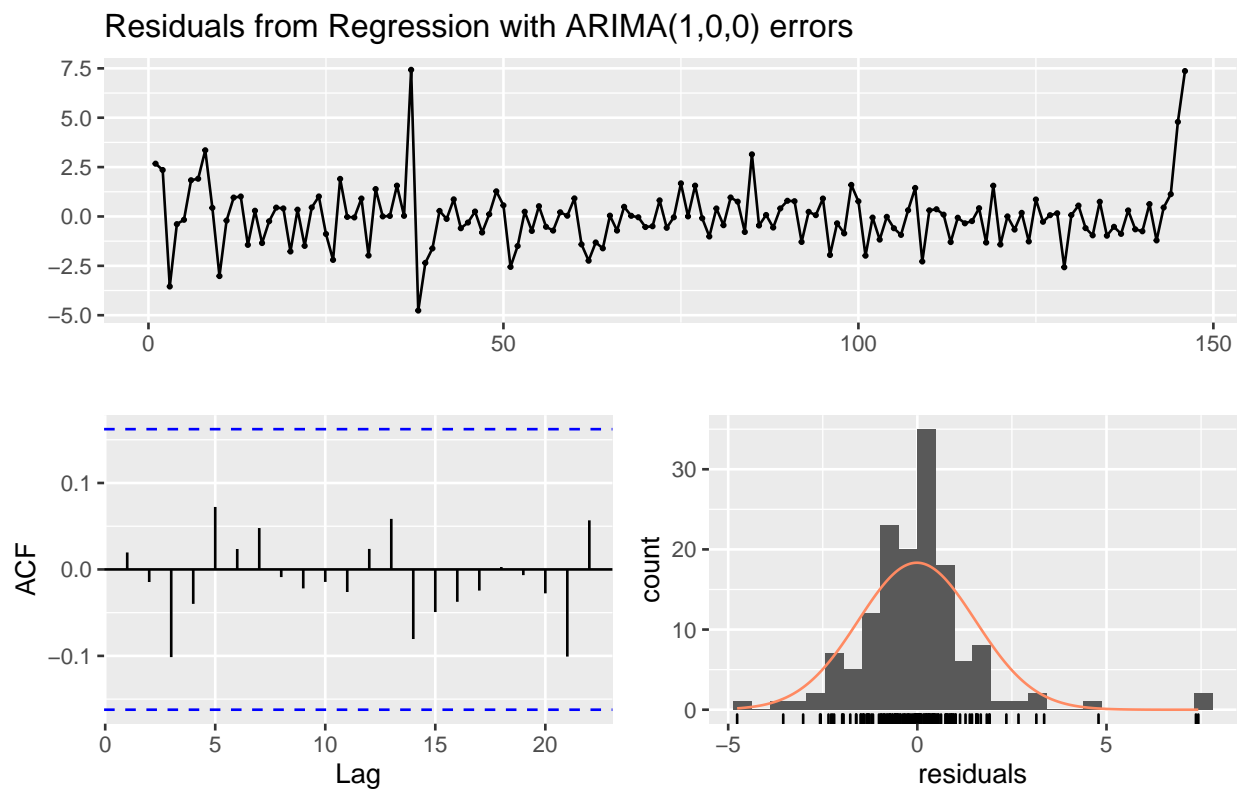
```
## Series: y
## Regression with ARIMA(1,0,0) errors
##
```

```
## Coefficients:
##          ar1 intercept 'Avicultura de Corte' Pescado avp9 b1
##          0.4823    0.5436                0.5648 -0.1257 0.1491 0.1027
## s.e.    0.1250    0.2797                0.1101  0.0892 0.0492 0.1226
##
## sigma^2 estimated as 2.485: log likelihood=-270.68
## AIC=555.36 AICc=556.17 BIC=576.24
```

```
coeftest(fit4)
```

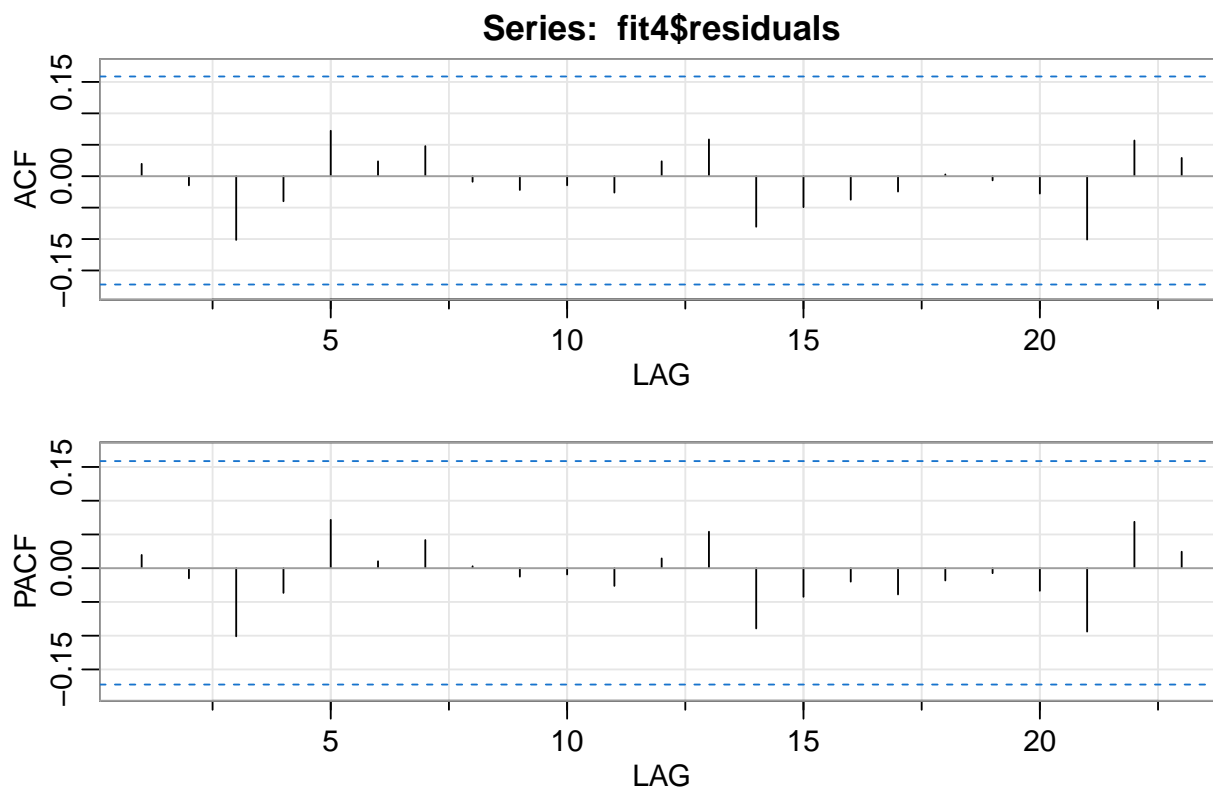
```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## ar1            0.482252   0.124956  3.8594 0.0001137 ***
## intercept      0.543622   0.279737  1.9433 0.0519760 .
## 'Avicultura de Corte' 0.564759   0.110114  5.1289 2.915e-07 ***
## Pescado        -0.125731   0.089156 -1.4102 0.1584680
## avp9            0.149073   0.049215  3.0290 0.0024534 **
## b1              0.102674   0.122567  0.8377 0.4022023
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
checkresiduals(fit4)
```



```
##
## Ljung-Box test
##
## data: Residuals from Regression with ARIMA(1,0,0) errors
## Q* = 3.2481, df = 4, p-value = 0.5172
##
## Model df: 6. Total lags used: 10
```

```
acf2(fit4$residuals)
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.02 -0.01 -0.1 -0.04 0.07 0.02 0.05 -0.01 -0.02 -0.01 -0.03 0.02 0.06
## PACF 0.02 -0.01 -0.1 -0.04 0.07 0.01 0.04 0.00 -0.01 -0.01 -0.03 0.01 0.05
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF  -0.08 -0.05 -0.04 -0.02 0.00 -0.01 -0.03 -0.10 0.06 0.03
## PACF -0.09 -0.04 -0.02 -0.04 -0.02 -0.01 -0.03 -0.09 0.07 0.02
```

```
fit5 <- tirar_variaveis(1, 0, 0, xx, y)
fit5[[1]]
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
```



```
## ar1                0.547259    0.087657    6.2432 4.288e-10 ***
## intercept          0.584360    0.293969    1.9878  0.04683 *
## 'Avicultura de Corte' 0.560426    0.106041    5.2850 1.257e-07 ***
## avp9               0.132716    0.047193    2.8122  0.00492 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

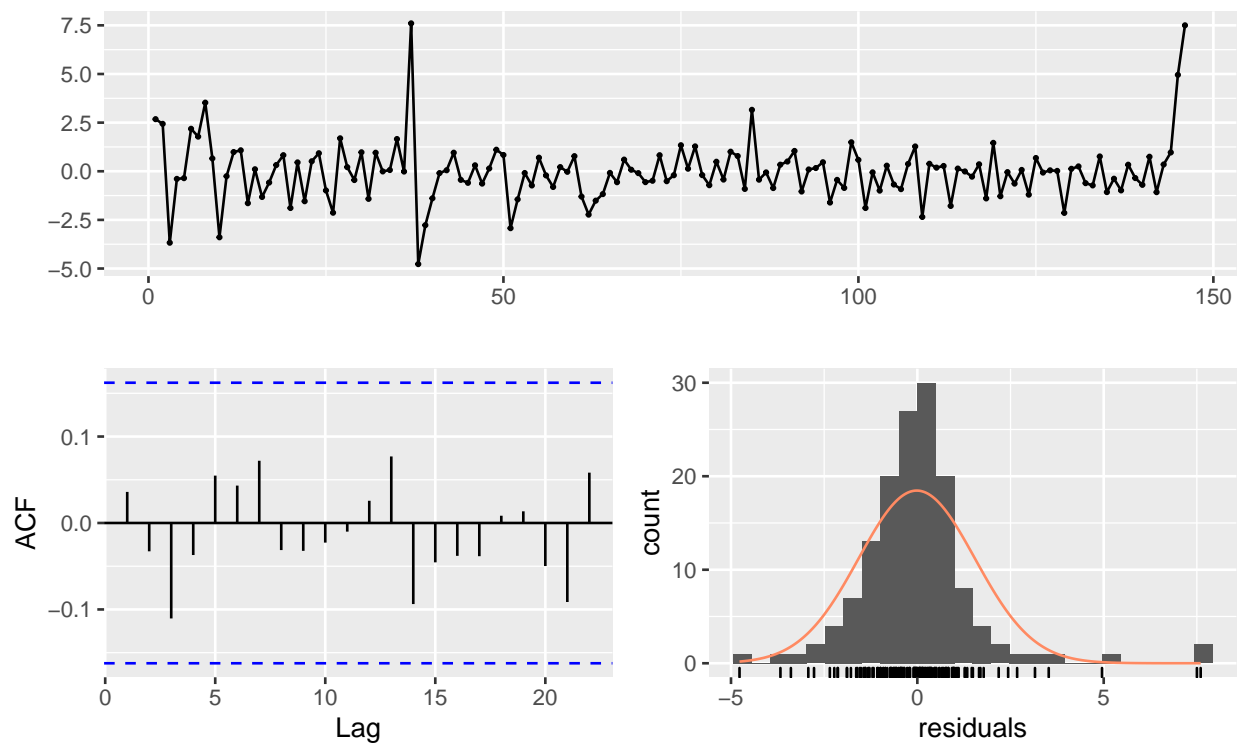
```
xx <- fit5[2]
xx<- xx[[1]]
```

```
fit6 = Arima(y,order=c(1,0,0),xreg=xx,fixed=c(NA,NA, NA, NA))
cof.fit6 = coeftest(fit6)
cof.fit6
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## ar1            0.547259    0.087657    6.2432 4.288e-10 ***
## intercept      0.584360    0.293969    1.9878  0.04683 *
## 'Avicultura de Corte' 0.560426    0.106041    5.2850 1.257e-07 ***
## avp9           0.132716    0.047193    2.8122  0.00492 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

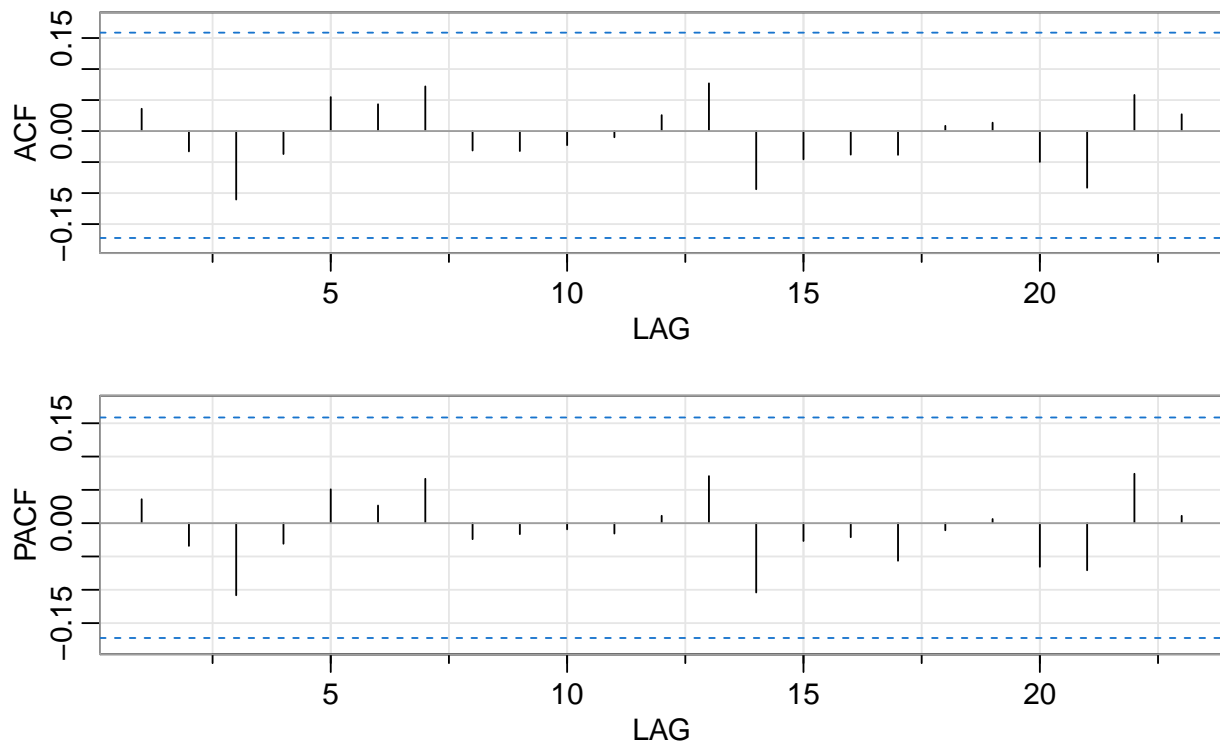
```
checkresiduals(fit6)
```

Residuals from Regression with ARIMA(1,0,0) errors



```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(1,0,0) errors
## Q* = 4.357, df = 6, p-value = 0.6285
##
## Model df: 4.    Total lags used: 10
```

```
acf2(fit6$residuals, main = "")
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.04 -0.03 -0.11 -0.04 0.05 0.04 0.07 -0.03 -0.03 -0.02 -0.01  0.03  0.08
## PACF 0.04 -0.03 -0.11 -0.03 0.05 0.03 0.07 -0.02 -0.02 -0.01 -0.02  0.01  0.07
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF  -0.09 -0.05 -0.04 -0.04  0.01  0.01 -0.05 -0.09  0.06  0.03
## PACF -0.10 -0.03 -0.02 -0.06 -0.01  0.01 -0.07 -0.07  0.07  0.01
```

Modelo da Avicultura de Corte

Estruturando a base

```
#Estruturando a base
df1<- funcao_lags(data_cut, data_cut$'Avicultura de Corte', 'cort1', 1)
df1 <- funcao_lags(df1, df1$'Avicultura de Postura', 'pos12', 12)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov1', 1)
df1 <- funcao_lags(df1, df1$Pescado, 'pes4', 4)
df1 <- funcao_lags(df1, df1$Pescado, 'pes9', 9)
df1 <- funcao_lags(df1, df1$Suinocultura, 'sui1', 1)
df1 <- funcao_lags(df1, df1$Suinocultura, 'sui6', 6)

df2 <- na.omit(df1)
```

Separando variável preditora e as covariáveis

```
#Separando variável preditora e as covariáveis
x = model.matrix('Avicultura de Corte'~.,df2)[,-1]
y = df2$'Avicultura de Corte'
```

Regressão classica no contexto de Séries Temporais

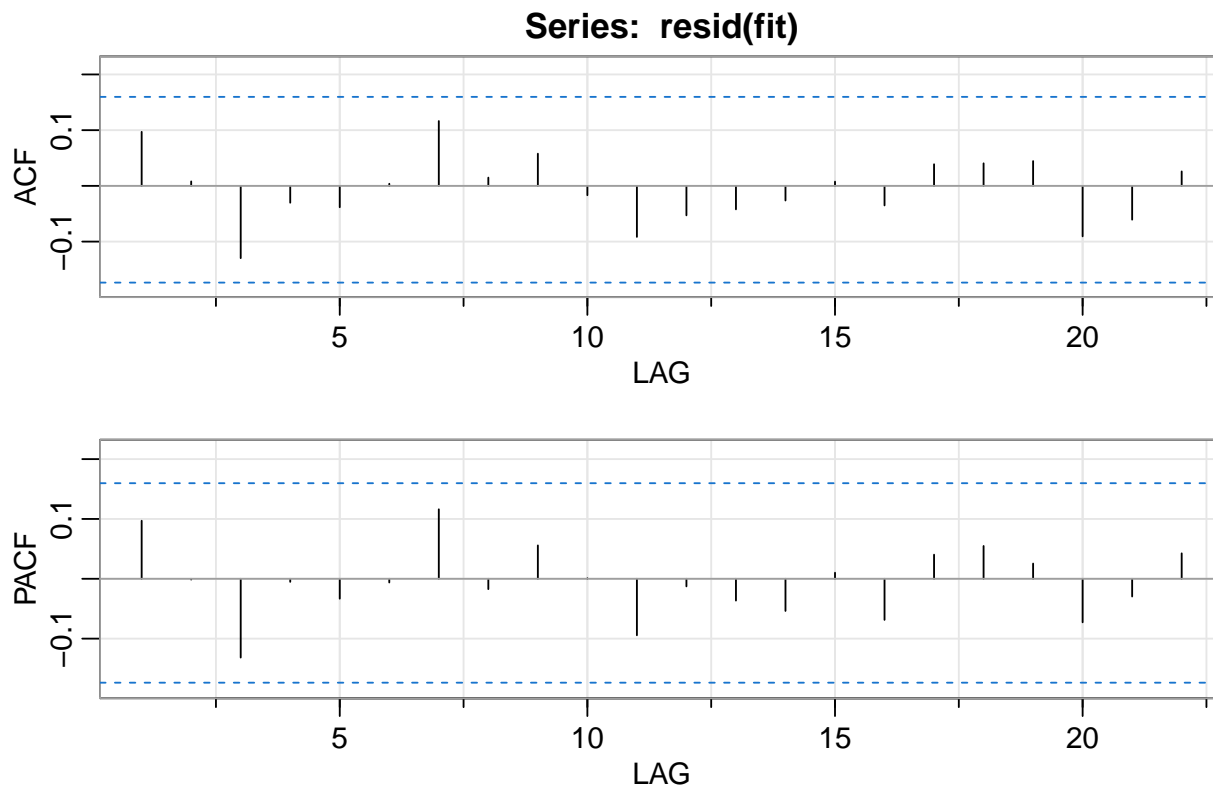
Criando o modelo de Regressão Simples

```
#Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.8583 -0.5435 -0.0324  0.5123  3.4823
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -0.01212     0.13955  -0.087 0.930894
## xBovinocultura    0.22080     0.05196   4.249 4.05e-05 ***
## x'Avicultura de Postura' 0.12991     0.03793   3.425 0.000822 ***
## xPescado         0.07105     0.06226   1.141 0.255841
## xLácteos         0.24253     0.07549   3.213 0.001655 **
## xSuinocultura    0.19667     0.13949   1.410 0.160939
## xcort1           0.33941     0.07225   4.698 6.56e-06 ***
## xpos12          -0.10059     0.03611  -2.785 0.006139 **
## xbov1            0.07239     0.06584   1.099 0.273628
## xpes4           -0.06147     0.06412  -0.959 0.339505
## xpes9            0.15784     0.06198   2.547 0.012035 *
## xsui1           -0.01789     0.13031  -0.137 0.891035
## xsui6           -0.44583     0.11305  -3.944 0.000130 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9766 on 131 degrees of freedom
## Multiple R-squared:  0.5835, Adjusted R-squared:  0.5454
## F-statistic: 15.3 on 12 and 131 DF,  p-value: < 2.2e-16
```

Análise dos Resíduos

```
#Análise dos Resíduos
acf2(resid(fit))
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF   0.1 0.01 -0.13 -0.03 -0.04  0.00 0.12  0.01 0.06 -0.02 -0.09 -0.05 -0.04
## PACF  0.1 0.00 -0.13 -0.01 -0.03 -0.01 0.12 -0.02 0.06  0.00 -0.09 -0.01 -0.04
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## ACF  -0.03  0.01 -0.04  0.04  0.04  0.04 -0.09 -0.06  0.03
## PACF -0.05  0.01 -0.07  0.04  0.05  0.03 -0.07 -0.03  0.04
```

Seleção de variáveis

```
#Seleção de variáveis
fit2 <- tirar_variaveis(0, 0, 0, x, y)
xx <- fit2[2]
xx <- xx[[1]]

fit3 = Arima(y,order=c(0,0,0), include.mean = FALSE, xreg=xx)
fit3
```

```
## Series: y
## Regression with ARIMA(0,0,0) errors
##
## Coefficients:
##      Bovinocultura  'Avicultura de Postura'  Lácteos   cort1    pos12    pes9
##              0.2870                0.1343    0.2003  0.4368  -0.0781  0.195
## s.e.              0.0401                0.0350    0.0681  0.0561   0.0329  0.053
##              sui6
##             -0.4269
```

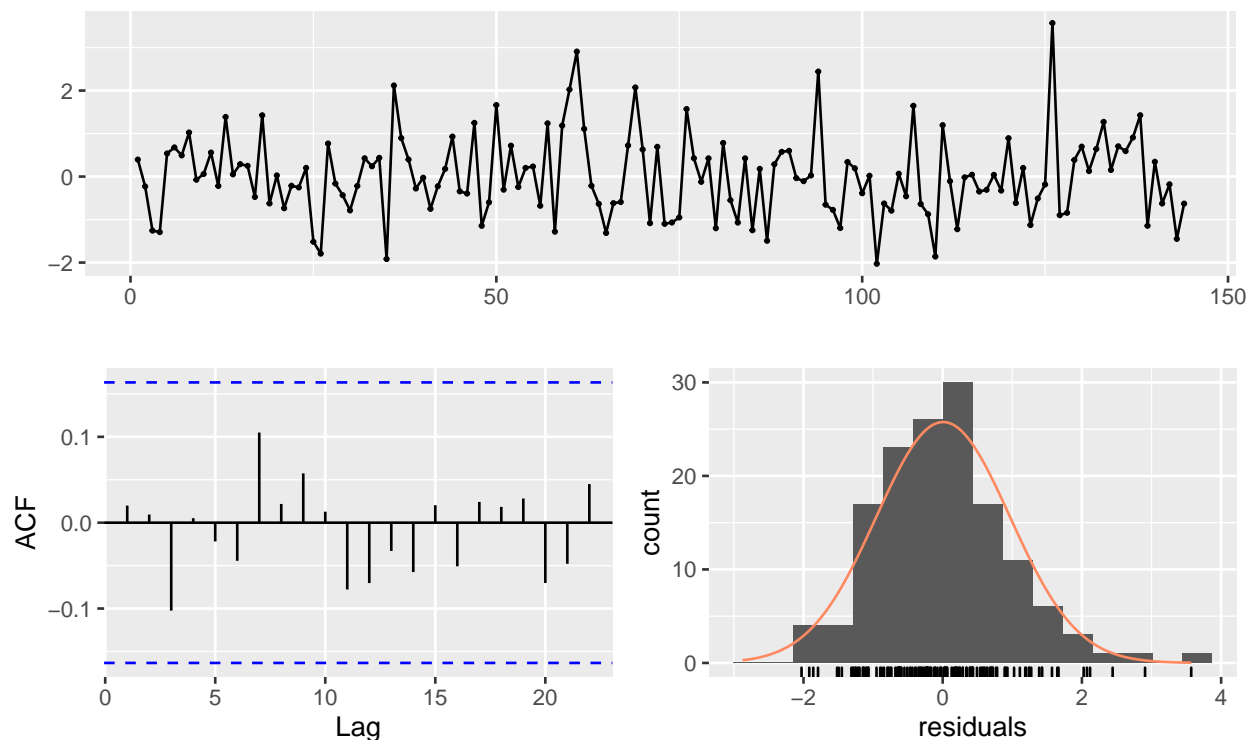
```
## s.e.    0.0992
##
## sigma^2 estimated as 0.9627:  log likelihood=-198
## AIC=412   AICc=413.07   BIC=435.76
```

```
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value  Pr(>|z|)
## Bovinocultura      0.286983   0.040122   7.1527 8.509e-13 ***
## 'Avicultura de Postura' 0.134314   0.035007   3.8368 0.0001247 ***
## Lácteos              0.200323   0.068070   2.9429 0.0032516 **
## cort1                0.436756   0.056084   7.7875 6.833e-15 ***
## pos12               -0.078065   0.032944  -2.3696 0.0178072 *
## pes9                 0.195018   0.053005   3.6793 0.0002339 ***
## sui6                -0.426896   0.099200  -4.3034 1.682e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
checkresiduals(fit3)
```

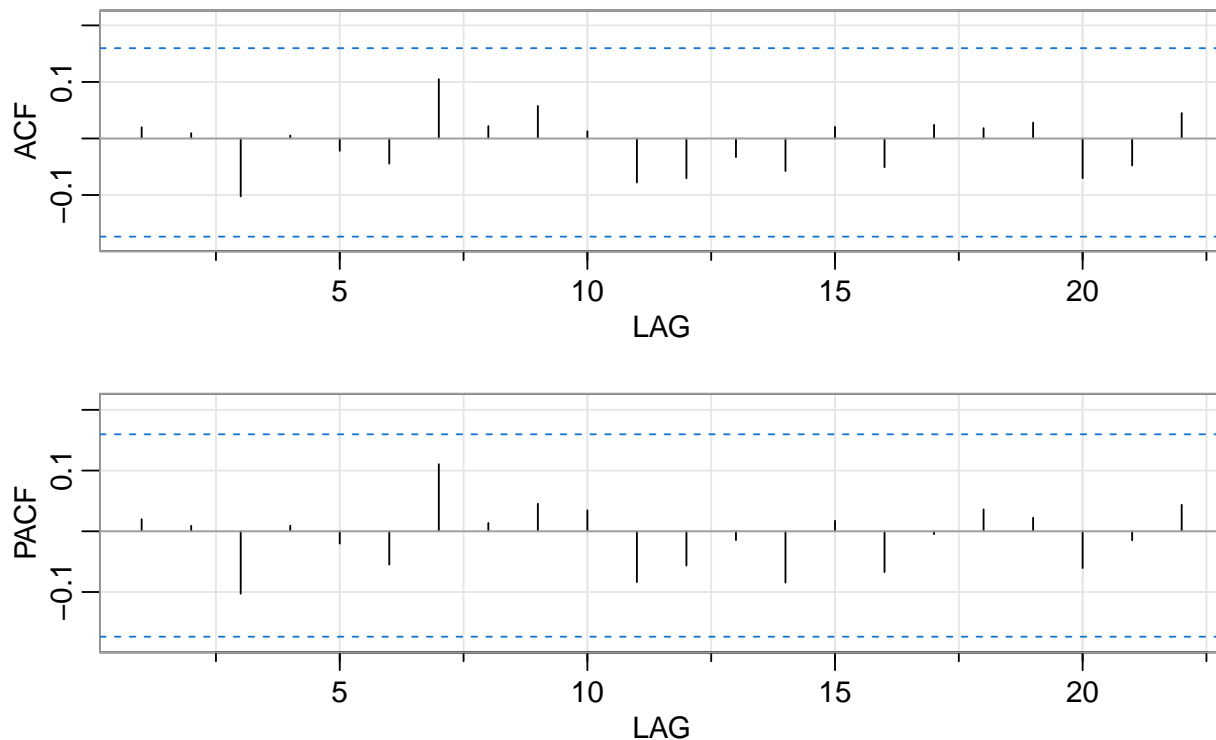
Residuals from Regression with ARIMA(0,0,0) errors



```
##
```

```
## Ljung-Box test
##
## data: Residuals from Regression with ARIMA(0,0,0) errors
## Q* = 4.3146, df = 3, p-value = 0.2294
##
## Model df: 7. Total lags used: 10
```

```
acf2(fit3$residuals, main = "")
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.02 0.01 -0.1 0.01 -0.02 -0.04 0.10 0.02 0.06 0.01 -0.08 -0.07 -0.03
## PACF 0.02 0.01 -0.1 0.01 -0.02 -0.05 0.11 0.01 0.05 0.03 -0.08 -0.06 -0.01
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## ACF  -0.06 0.02 -0.05 0.02 0.02 0.03 -0.07 -0.05 0.04
## PACF -0.08 0.02 -0.07 0.00 0.04 0.02 -0.06 -0.01 0.04
```

Modelo da Pescados

Estruturando a base

```
# Estruturando a base
df1<- funcao_lags(data_cut, data_cut$Pescado, 'pes1', 1)
df1 <- funcao_lags(df1, df1$Pescado, 'pes5', 5)
df1 <- funcao_lags(df1, df1$Pescado, 'pes12', 12)
```

```

df1 <- funcao_lags(df1, df1$'Avicultura de Corte', 'cort3', 3)
df1 <- funcao_lags(df1, df1$'Avicultura de Corte', 'cort8', 8)

df1 <- funcao_lags(df1, df1$'Avicultura de Postura', 'pos2', 2)
df1 <- funcao_lags(df1, df1$'Avicultura de Postura', 'pos9', 9)

df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov1', 1)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov3', 3)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov7', 7)

df1 <- funcao_lags(df1, df1$Lácteos, 'lact2', 2)
df1 <- funcao_lags(df1, df1$Lácteos, 'lact8', 8)

df1 <- funcao_lags(df1, df1$Suinocultura, 'sui3', 3)

df2 <- na.omit(df1)

```

Separando variável preditora e as covariáveis

```

#Separando variável preditora e as covariáveis
x = model.matrix(Pescado~.,df2)[-1]
y = df2$Pescado

```

Regressão classifica no contexto de Séries Temporais

Criando o modelo de Regressão Simples

```

# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.8416 -0.7307 -0.0757  0.6792  3.1091
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.19703     0.16044   1.228 0.221743
## xBovinocultura  -0.03365     0.06031  -0.558 0.577890
## x'Avicultura de Corte'  0.01262     0.08765   0.144 0.885759

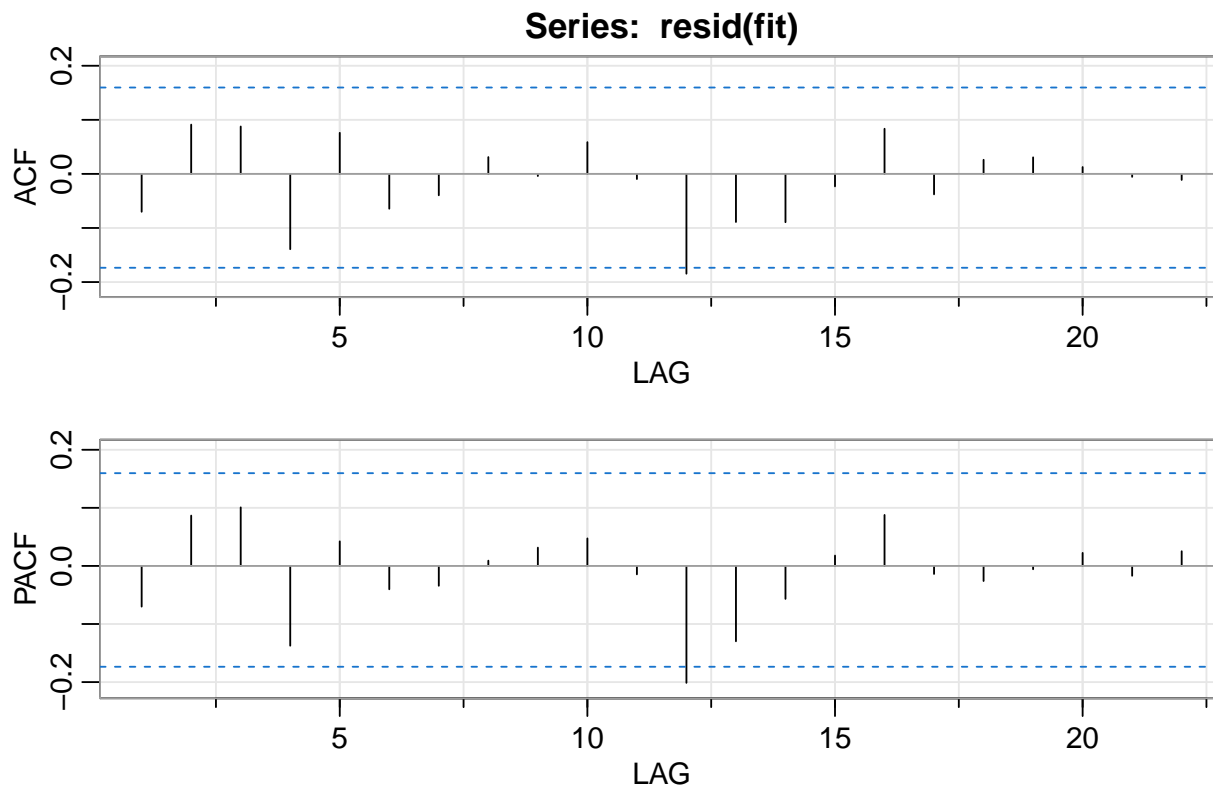
```



```
## x'Avicultura de Postura'  0.14380    0.04089    3.517 0.000609 ***
## xLácteos                 -0.11286    0.09287   -1.215 0.226550
## xSuinocultura            0.11153    0.14706    0.758 0.449621
## xpes1                    -0.03033    0.06781   -0.447 0.655479
## xpes5                    -0.08437    0.07483   -1.128 0.261683
## xpes12                   0.30991    0.07164    4.326 3.08e-05 ***
## xcort3                   0.07747    0.07984    0.970 0.333785
## xcort8                   -0.14097    0.07260   -1.942 0.054438 .
## xpos2                    -0.03105    0.04007   -0.775 0.439934
## xpos9                    0.09715    0.03980    2.441 0.016048 *
## xbov1                    0.16976    0.07257    2.339 0.020910 *
## xbov3                    -0.05010    0.06816   -0.735 0.463668
## xbov7                    -0.12174    0.05980   -2.036 0.043905 *
## xlact2                   0.02538    0.09274    0.274 0.784790
## xlact8                   0.05811    0.08427    0.690 0.491745
## xsui3                    0.37341    0.15003    2.489 0.014128 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.098 on 125 degrees of freedom
## Multiple R-squared:  0.5513, Adjusted R-squared:  0.4867
## F-statistic: 8.534 on 18 and 125 DF,  p-value: 1.673e-14
```

Análise dos Resíduos

```
# Análise dos Resíduos
acf2(resid(fit))
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  -0.07 0.09 0.09 -0.14 0.08 -0.06 -0.04 0.03 0.00  0.06 -0.01 -0.18 -0.09
## PACF -0.07 0.09 0.10 -0.14 0.04 -0.04 -0.03 0.01 0.03  0.05 -0.01 -0.20 -0.13
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## ACF  -0.09 -0.02  0.08 -0.04  0.03  0.03  0.01 -0.01 -0.01
## PACF -0.06  0.02  0.09 -0.01 -0.03 -0.01  0.02 -0.02  0.03
```

Regressão com erros autocorrelacionais

Análise dos resíduos e seleção de variáveis de acordo com p-valor

```
# Análise dos resíduos e seleção de variáveis de acordo com p-valor
y = ts(y, frequency=12)

x = x[,-1]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## sar1         -0.386944   0.091562 -4.2261 2.378e-05 ***
## intercept      0.080072   0.119976  0.6674 0.5045201
## 'Avicultura de Corte' 0.021593   0.070335  0.3070 0.7588441
```

```
## 'Avicultura de Postura' 0.116637 0.033488 3.4830 0.0004959 ***
## Lácteos -0.062973 0.080753 -0.7798 0.4354975
## Suinocultura 0.155301 0.120650 1.2872 0.1980220
## pes1 -0.037597 0.052277 -0.7192 0.4720305
## pes5 -0.095328 0.059900 -1.5915 0.1115067
## pes12 0.507059 0.069068 7.3415 2.112e-13 ***
## cort3 0.077964 0.068351 1.1406 0.2540252
## cort8 -0.099856 0.067674 -1.4755 0.1400699
## pos2 -0.012863 0.032304 -0.3982 0.6905015
## pos9 0.065823 0.031207 2.1092 0.0349240 *
## bov1 0.095679 0.063358 1.5101 0.1310108
## bov3 -0.025267 0.056244 -0.4492 0.6532543
## bov7 -0.103807 0.050848 -2.0415 0.0411989 *
## lact2 0.003111 0.079860 0.0390 0.9689257
## lact8 0.033576 0.077945 0.4308 0.6666430
## sui3 0.345969 0.120310 2.8757 0.0040319 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-15]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
## Estimate Std. Error z value Pr(>|z|)
## sar1 -0.387179 0.091333 -4.2392 2.243e-05 ***
## intercept 0.081189 0.116486 0.6970 0.4858110
## 'Avicultura de Corte' 0.021848 0.070023 0.3120 0.7550344
## 'Avicultura de Postura' 0.116206 0.031601 3.6772 0.0002358 ***
## Lácteos -0.061895 0.075859 -0.8159 0.4145439
## Suinocultura 0.155191 0.120610 1.2867 0.1981900
## pes1 -0.038027 0.051090 -0.7443 0.4566819
## pes5 -0.095203 0.059810 -1.5917 0.1114423
## pes12 0.507119 0.069034 7.3459 2.044e-13 ***
## cort3 0.077986 0.068345 1.1411 0.2538471
## cort8 -0.099416 0.066727 -1.4899 0.1362542
## pos2 -0.012825 0.032287 -0.3972 0.6912055
## pos9 0.065767 0.031172 2.1098 0.0348757 *
## bov1 0.095336 0.062735 1.5197 0.1285958
## bov3 -0.025241 0.056236 -0.4488 0.6535506
## bov7 -0.103724 0.050801 -2.0418 0.0411723 *
## lact8 0.033821 0.077687 0.4354 0.6633040
## sui3 0.346308 0.119977 2.8865 0.0038960 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-1]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
```

```
## z test of coefficients:
##
##
##           Estimate Std. Error z value Pr(>|z|)
## sar1          -0.384320   0.091107 -4.2184 2.461e-05 ***
## intercept       0.087499   0.114897  0.7615 0.4463318
## 'Avicultura de Postura' 0.117141  0.031538  3.7142 0.0002038 ***
## Lácteos         -0.058925   0.075323 -0.7823 0.4340391
## Suinocultura     0.160818   0.119384  1.3471 0.1779589
## pes1            -0.040538   0.050535 -0.8022 0.4224562
## pes5            -0.096844   0.059644 -1.6237 0.1044420
## pes12           0.505835   0.069119  7.3183 2.511e-13 ***
## cort3           0.074506   0.067497  1.1038 0.2696650
## cort8           -0.100503   0.066625 -1.5085 0.1314272
## pos2            -0.013420   0.032278 -0.4158 0.6775852
## pos9            0.067293   0.030822  2.1833 0.0290167 *
## bov1            0.103928   0.056423  1.8419 0.0654843 .
## bov3            -0.025070   0.056307 -0.4452 0.6561505
## bov7            -0.109781   0.046989 -2.3363 0.0194757 *
## lact8           0.029144   0.076293  0.3820 0.7024574
## sui3            0.356336   0.115786  3.0775 0.0020872 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-14]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##
##           Estimate Std. Error z value Pr(>|z|)
## sar1          -0.388147   0.090164 -4.3049 1.671e-05 ***
## intercept       0.095826   0.112606  0.8510 0.394777
## 'Avicultura de Postura' 0.118704  0.031256  3.7978 0.000146 ***
## Lácteos         -0.058338   0.075318 -0.7746 0.438605
## Suinocultura     0.157438   0.118989  1.3231 0.185792
## pes1            -0.036520   0.049362 -0.7398 0.459399
## pes5            -0.097461   0.059586 -1.6356 0.101919
## pes12           0.513113   0.066348  7.7336 1.045e-14 ***
## cort3           0.073818   0.067452  1.0944 0.273796
## cort8           -0.096605   0.065857 -1.4669 0.142403
## pos2            -0.011675   0.031917 -0.3658 0.714510
## pos9            0.070328   0.029759  2.3633 0.018114 *
## bov1            0.103383   0.056372  1.8340 0.066660 .
## bov3            -0.022418   0.055839 -0.4015 0.688067
## bov7            -0.112367   0.046468 -2.4182 0.015598 *
## sui3            0.351878   0.115074  3.0578 0.002229 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-9]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##               Estimate Std. Error z value Pr(>|z|)
## sar1          -0.390935   0.089362 -4.3747 1.216e-05 ***
## intercept      0.096283   0.112406  0.8566 0.391686
## 'Avicultura de Postura' 0.120786   0.030699  3.9345 8.338e-05 ***
## Lácteos        -0.063597   0.073916 -0.8604 0.389575
## Suinocultura    0.154805   0.118734  1.3038 0.192303
## pes1          -0.040696   0.047980 -0.8482 0.396326
## pes5          -0.104471   0.056397 -1.8524 0.063964 .
## pes12          0.517458   0.064975  7.9639 1.667e-15 ***
## cort3          0.072869   0.067380  1.0815 0.279492
## cort8         -0.097380   0.065850 -1.4788 0.139192
## pos9           0.070694   0.029732  2.3777 0.017421 *
## bov1           0.104262   0.056282  1.8525 0.063952 .
## bov3          -0.021411   0.055754 -0.3840 0.700960
## bov7          -0.112548   0.046456 -2.4227 0.015406 *
## sui3           0.349353   0.114804  3.0430 0.002342 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-11]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##               Estimate Std. Error z value Pr(>|z|)
## sar1          -0.392673   0.088904 -4.4168 1.002e-05 ***
## intercept      0.092348   0.111873  0.8255 0.409104
## 'Avicultura de Postura' 0.117943   0.029764  3.9625 7.415e-05 ***
## Lácteos        -0.060075   0.073328 -0.8193 0.412638
## Suinocultura    0.156577   0.118658  1.3196 0.186979
## pes1          -0.042151   0.047810 -0.8816 0.377972
## pes5          -0.102738   0.056211 -1.8277 0.067592 .
## pes12          0.519187   0.064688  8.0260 1.007e-15 ***
## cort3          0.063206   0.062513  1.0111 0.311977
## cort8         -0.098137   0.065817 -1.4911 0.135945
## pos9           0.070944   0.029689  2.3895 0.016869 *
## bov1           0.101801   0.055946  1.8196 0.068815 .
## bov7          -0.112213   0.046453 -2.4156 0.015708 *
## sui3           0.335663   0.109074  3.0774 0.002088 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-2]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
```

```
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## sar1          -0.400868   0.087551 -4.5787 4.679e-06 ***
## intercept      0.071346   0.108529  0.6574 0.5109328
## 'Avicultura de Postura' 0.112130  0.028898  3.8802 0.0001044 ***
## Suinocultura    0.147507   0.118103  1.2490 0.2116763
## pes1          -0.041784   0.047712 -0.8758 0.3811637
## pes5          -0.110446   0.055348 -1.9955 0.0459902 *
## pes12          0.526696   0.063928  8.2389 < 2.2e-16 ***
## cort3          0.062889   0.062508  1.0061 0.3143661
## cort8         -0.098307   0.065984 -1.4899 0.1362606
## pos9           0.071948   0.029595  2.4311 0.0150537 *
## bov1           0.106356   0.055664  1.9107 0.0560455 .
## bov7          -0.119520   0.045542 -2.6244 0.0086805 **
## sui3           0.334402   0.108969  3.0688 0.0021494 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-3]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## sar1          -0.398561   0.088489 -4.5041 6.667e-06 ***
## intercept      0.053521   0.106943  0.5005 0.6167476
## 'Avicultura de Postura' 0.108768  0.028746  3.7837 0.0001545 ***
## Suinocultura    0.151192   0.118435  1.2766 0.2017491
## pes5          -0.102299   0.054775 -1.8676 0.0618157 .
## pes12          0.522676   0.064592  8.0920 5.869e-16 ***
## cort3          0.059915   0.062636  0.9566 0.3387898
## cort8         -0.095019   0.066096 -1.4376 0.1505515
## pos9           0.071221   0.029727  2.3958 0.0165836 *
## bov1           0.102061   0.055734  1.8312 0.0670717 .
## bov7          -0.120174   0.045699 -2.6297 0.0085467 **
## sui3           0.317169   0.107541  2.9493 0.0031851 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-5]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## sar1          -0.398172   0.088518 -4.4982 6.854e-06 ***
## intercept      0.060722   0.107058  0.5672 0.5705875
```

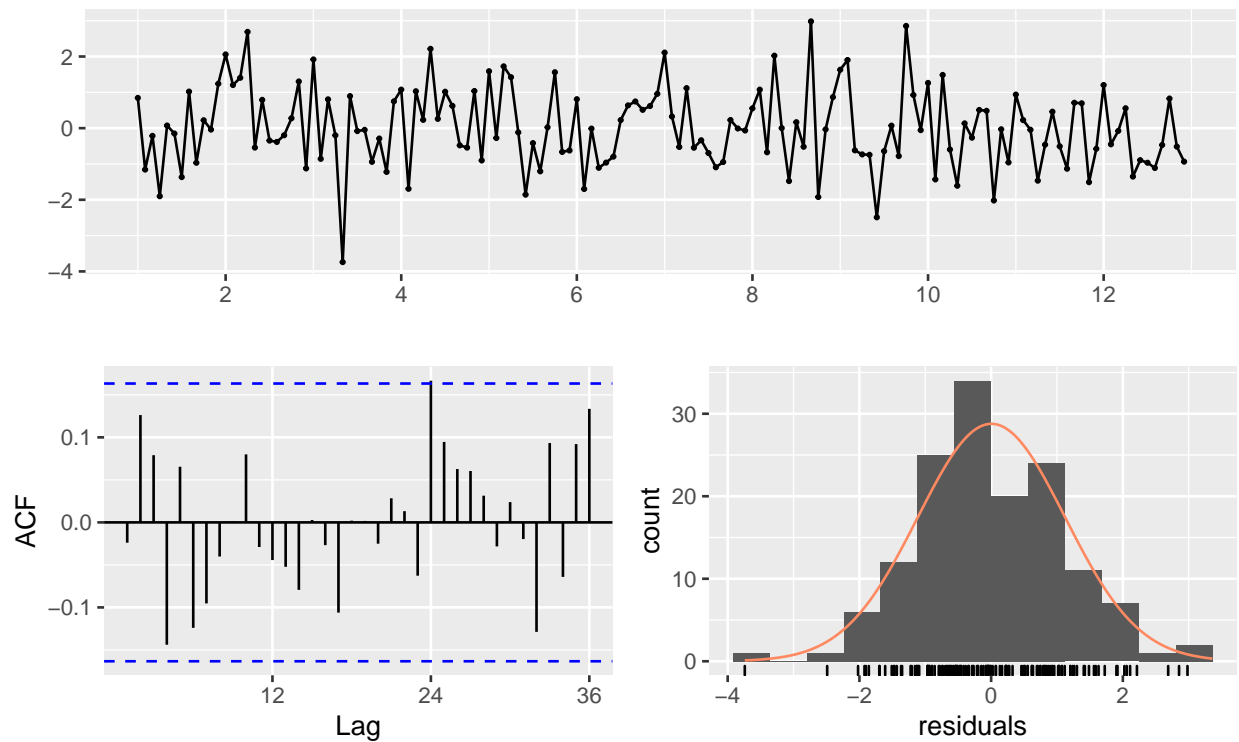
```
## 'Avicultura de Postura' 0.112567 0.028586 3.9378 8.223e-05 ***
## Suinocultura          0.163490 0.118145 1.3838 0.1664180
## pes5                  -0.106665 0.054751 -1.9482 0.0513943 .
## pes12                 0.535268 0.063461 8.4345 < 2.2e-16 ***
## cort8                 -0.102429 0.065732 -1.5583 0.1191654
## pos9                  0.072864 0.029770 2.4475 0.0143834 *
## bov1                  0.091020 0.054774 1.6617 0.0965686 .
## bov7                  -0.119608 0.045864 -2.6079 0.0091094 **
## sui3                  0.348003 0.103094 3.3756 0.0007366 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-4]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## sar1          0.2469874 0.1061663 2.3264 0.0199962 *
## intercept     0.4025207 0.1625312 2.4766 0.0132650 *
## 'Avicultura de Postura' 0.1477883 0.0400297 3.6920 0.0002225 ***
## Suinocultura  -0.0079504 0.1475616 -0.0539 0.9570319
## pes5          -0.1227962 0.0783012 -1.5683 0.1168216
## cort8         -0.1584009 0.0703558 -2.2514 0.0243585 *
## pos9           0.1308314 0.0400853 3.2638 0.0010992 **
## bov1           0.1896427 0.0636054 2.9816 0.0028679 **
## bov7          -0.1488028 0.0572052 -2.6012 0.0092895 **
## sui3           0.3490096 0.1297387 2.6901 0.0071431 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

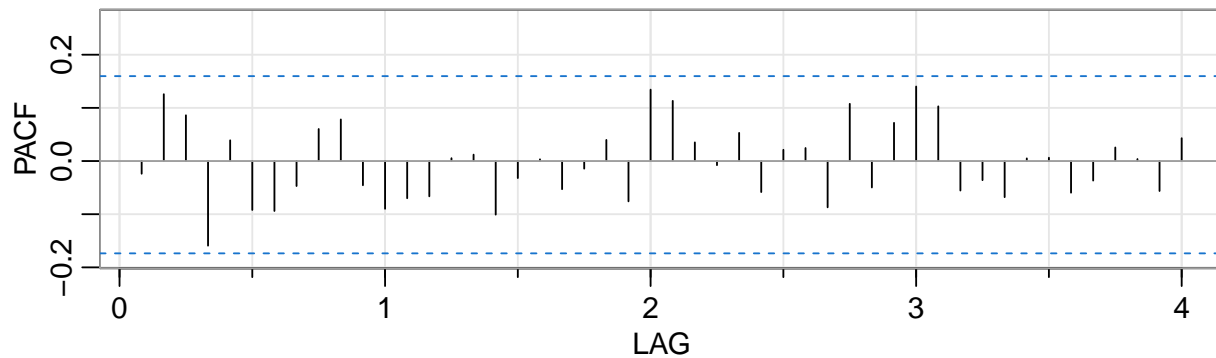
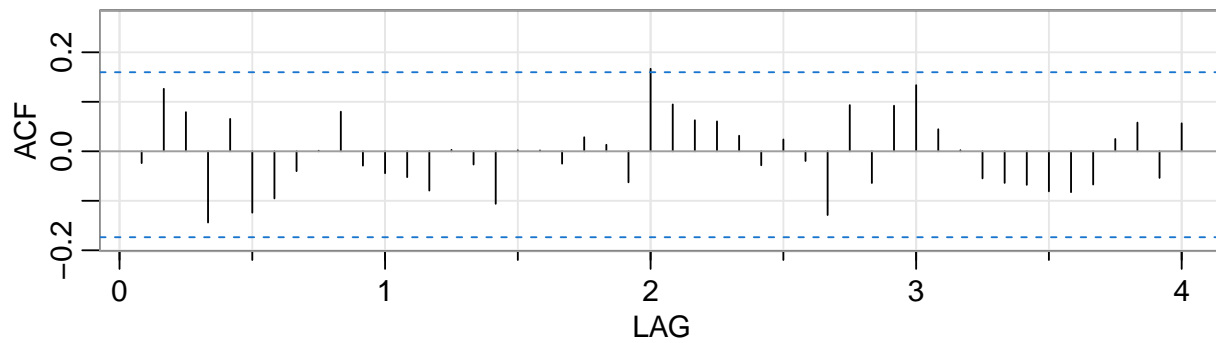
```
checkresiduals(fit3)
```

Residuals from Regression with ARIMA(0,0,0)(1,0,0)[12] errors



```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(0,0,0)(1,0,0)[12] errors
## Q* = 21.828, df = 14, p-value = 0.08222
##
## Model df: 10.   Total lags used: 24
```

```
acf2(fit3$residuals, main = "")
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  -0.02 0.13 0.08 -0.14 0.07 -0.12 -0.10 -0.04 0.00  0.08 -0.03 -0.04 -0.05
## PACF  -0.02 0.13 0.09 -0.16 0.04 -0.09 -0.09 -0.05 0.06  0.08 -0.05 -0.09 -0.07
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23] [,24] [,25]
## ACF  -0.08  0.00 -0.03 -0.11  0.00    0 -0.03  0.03  0.01 -0.06  0.17  0.09
## PACF  -0.07  0.01  0.01 -0.10 -0.03    0 -0.05 -0.01  0.04 -0.08  0.13  0.11
##      [,26] [,27] [,28] [,29] [,30] [,31] [,32] [,33] [,34] [,35] [,36] [,37]
## ACF   0.06  0.06  0.03 -0.03  0.02 -0.02 -0.13  0.09 -0.06  0.09  0.13  0.04
## PACF   0.04 -0.01  0.05 -0.06  0.02  0.02 -0.09  0.11 -0.05  0.07  0.14  0.10
##      [,38] [,39] [,40] [,41] [,42] [,43] [,44] [,45] [,46] [,47] [,48]
## ACF   0.00 -0.05 -0.06 -0.07 -0.08 -0.08 -0.07  0.02  0.06 -0.05  0.06
## PACF  -0.06 -0.04 -0.07  0.01  0.01 -0.06 -0.04  0.03  0.00 -0.06  0.04
```

```
x = x[,-2]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## sar1          0.245630   0.103130  2.3818 0.0172305 *
## intercept     0.400724   0.158954  2.5210 0.0117018 *
## 'Avicultura de Postura' 0.147907   0.039969  3.7005 0.0002151 ***
## pes5         -0.123470   0.077226 -1.5988 0.1098647
## cort8        -0.158979   0.069562 -2.2854 0.0222871 *
```

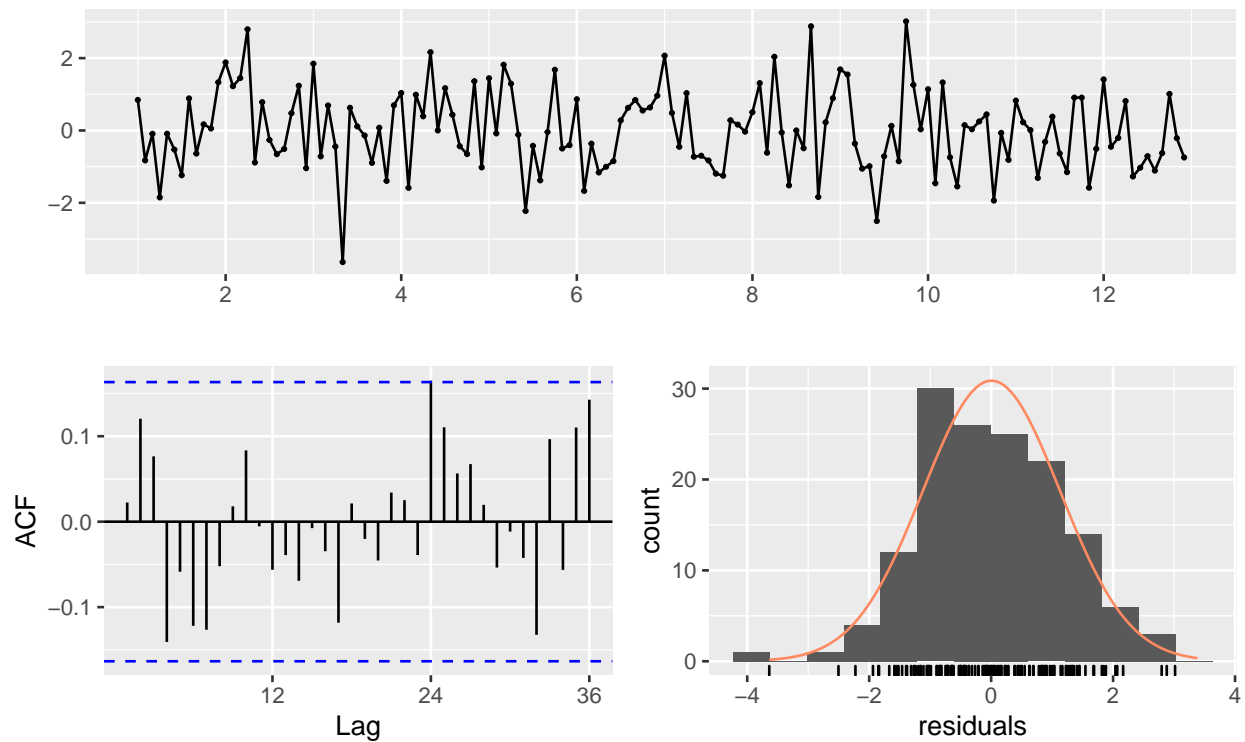
```
## pos9          0.130901    0.040054    3.2681 0.0010827 **
## bov1          0.187958    0.055461    3.3890 0.0007014 ***
## bov7         -0.148780    0.057202   -2.6010 0.0092965 **
## sui3          0.348588    0.129523    2.6913 0.0071169 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
x = x[,-2]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##              Estimate Std. Error z value  Pr(>|z|)
## sar1          0.309151    0.098927    3.1250 0.0017778 **
## intercept      0.331766    0.161882    2.0494 0.0404197 *
## 'Avicultura de Postura' 0.133601    0.039667    3.3681 0.0007570 ***
## cort8         -0.161858    0.070924   -2.2821 0.0224811 *
## pos9          0.135222    0.041512    3.2574 0.0011243 **
## bov1          0.198338    0.055331    3.5845 0.0003377 ***
## bov7         -0.152063    0.057899   -2.6264 0.0086302 **
## sui3          0.327597    0.130070    2.5186 0.0117818 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

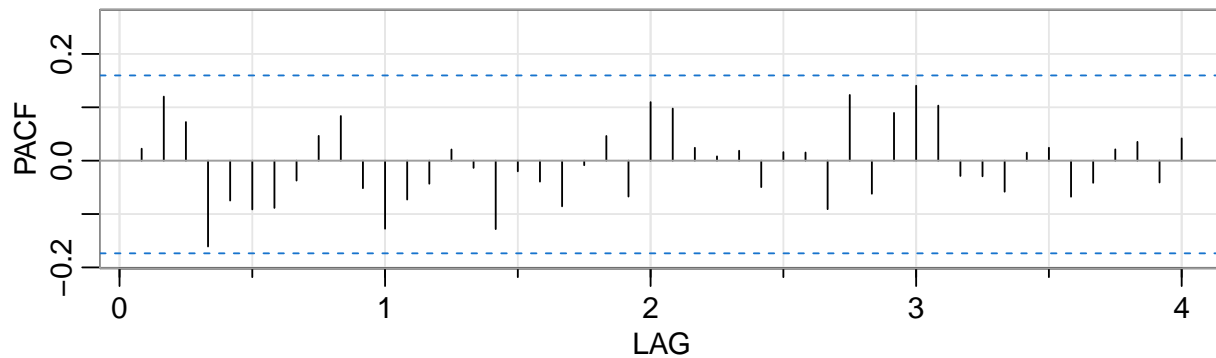
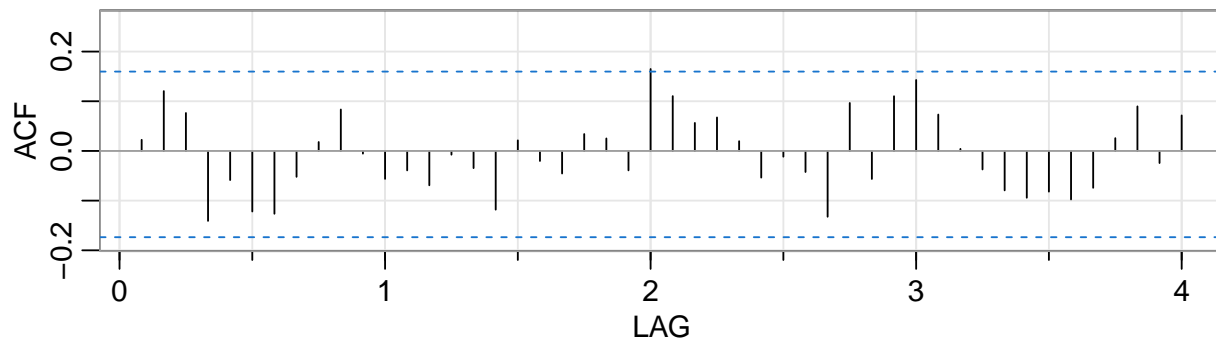
```
checkresiduals(fit3)
```

Residuals from Regression with ARIMA(0,0,0)(1,0,0)[12] errors



```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(0,0,0)(1,0,0)[12] errors
## Q* = 22.744, df = 16, p-value = 0.1208
##
## Model df: 8.   Total lags used: 24
```

```
acf2(fit3$residuals, main = "")
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.02 0.12 0.08 -0.14 -0.06 -0.12 -0.13 -0.05 0.02  0.08 -0.01 -0.06 -0.04
## PACF 0.02 0.12 0.07 -0.16 -0.07 -0.09 -0.09 -0.04 0.05  0.08 -0.05 -0.13 -0.07
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23] [,24] [,25]
## ACF -0.07 -0.01 -0.03 -0.12  0.02 -0.02 -0.05  0.03  0.03 -0.04  0.16  0.11
## PACF -0.04  0.02 -0.01 -0.13 -0.02 -0.04 -0.09 -0.01  0.05 -0.07  0.11  0.10
##      [,26] [,27] [,28] [,29] [,30] [,31] [,32] [,33] [,34] [,35] [,36] [,37]
## ACF  0.06  0.07  0.02 -0.05 -0.01 -0.04 -0.13  0.10 -0.06  0.11  0.14  0.07
## PACF 0.02  0.01  0.02 -0.05  0.02  0.02 -0.09  0.12 -0.06  0.09  0.14  0.10
##      [,38] [,39] [,40] [,41] [,42] [,43] [,44] [,45] [,46] [,47] [,48]
## ACF  0.00 -0.04 -0.08 -0.09 -0.08 -0.10 -0.07  0.03  0.09 -0.02  0.07
## PACF -0.03 -0.03 -0.06  0.02  0.02 -0.07 -0.04  0.02  0.04 -0.04  0.04
```

S

```
## function (object, brief, ...)
## {
##     UseMethod("S")
## }
## <bytecode: 0x000000001d3c43d8>
## <environment: namespace:car>
```

Modelo da Avicultura de postura

Estruturando a base

```
# Estruturando a base
df1<- funcao_lags(data_cut, data_cut$'Avicultura de Postura', 'avp1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Postura', 'avp12', 12)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc5', 5)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov3', 3)
df1 <- funcao_lags(df1, df1$Lácteos, 'lact11', 11)
df1 <- funcao_lags(df1, df1$Pescado, 'pes2', 2)
df1 <- funcao_lags(df1, df1$Pescado, 'pes9', 9)

df2 <- na.omit(df1)
```

Separando variável preditora e as covariáveis

```
#Separando variável preditora e as covariáveis
x = model.matrix('Avicultura de Postura'~.,df2)[,-1]
y = df2$'Avicultura de Postura'
```

Regressão classifica no contexto de Séries Temporais

Criando o modelo de Regressão Simples

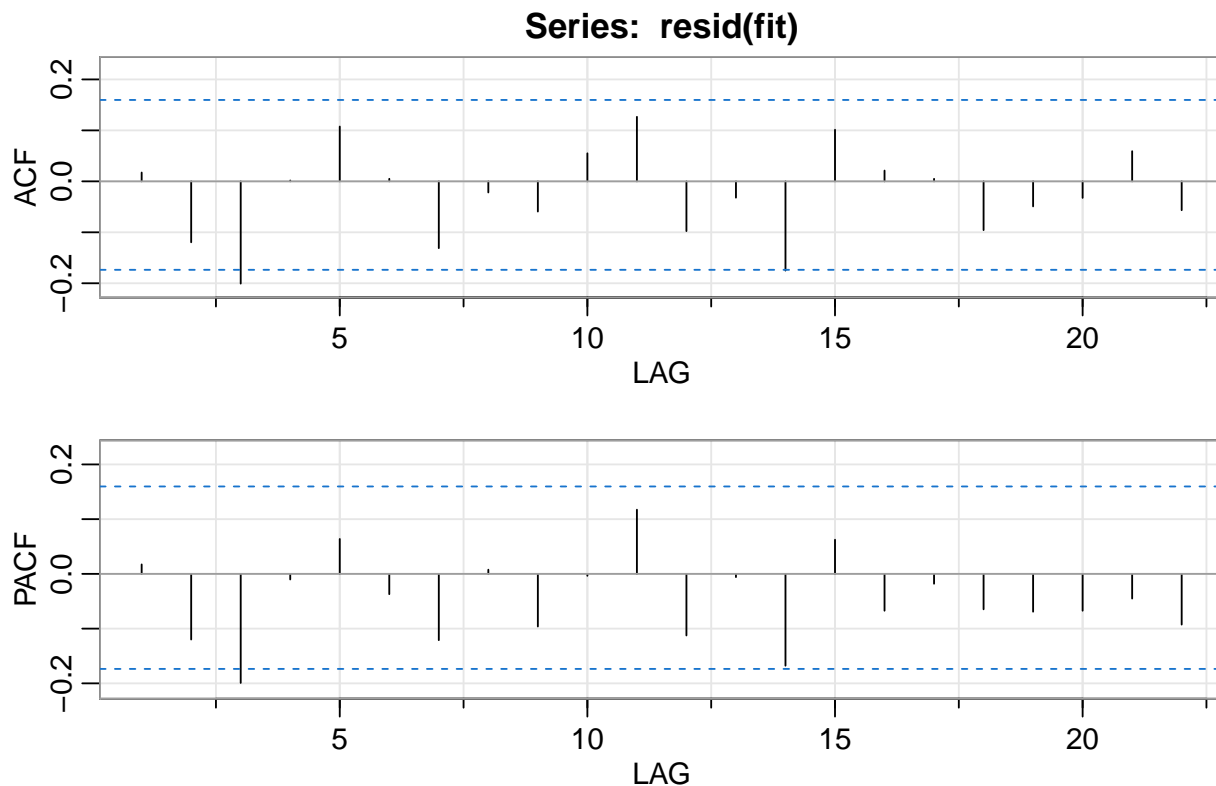
```
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.2151 -1.3755 -0.1872  1.4374  8.2788
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -0.01295    0.31733  -0.041  0.967509
## xBovinocultura -0.01770    0.10989  -0.161  0.872253
## x'Avicultura de Corte'  0.45460    0.16365   2.778  0.006274 **
## xPescado       0.35251    0.13562   2.599  0.010415 *
## xLácteos       0.16496    0.17453   0.945  0.346327
## xSuinocultura  -0.28456    0.27621  -1.030  0.304802
## xavp1          0.09421    0.07633   1.234  0.219312
## xavp12         0.31398    0.08246   3.808  0.000215 ***
## xavc5          0.31548    0.13972   2.258  0.025600 *
## xbov3          0.07400    0.12114   0.611  0.542366
## xlact11        0.11042    0.16012   0.690  0.491666
## xpes2         -0.02661    0.14349  -0.185  0.853182
## xpes9         -0.36608    0.14250  -2.569  0.011319 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2.178 on 131 degrees of freedom
## Multiple R-squared:  0.3902, Adjusted R-squared:  0.3343
## F-statistic: 6.984 on 12 and 131 DF,  p-value: 1.096e-09
```

Análise dos Resíduos

```
# Análise dos Resíduos
acf2(resid(fit))
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.02 -0.12 -0.2  0.00 0.11  0.01 -0.13 -0.02 -0.06  0.05  0.13 -0.10 -0.03
## PACF  0.02 -0.12 -0.2 -0.01 0.06 -0.04 -0.12  0.01 -0.10  0.00  0.12 -0.11 -0.01
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## ACF  -0.18  0.10  0.02  0.00 -0.10 -0.05 -0.03  0.06 -0.06
## PACF -0.17  0.06 -0.07 -0.02 -0.06 -0.07 -0.07 -0.05 -0.09
```

Regressão com erros autocorrelacionais

Análise dos resíduos e seleção de variáveis de acordo com p-valor

```
# Análise dos resíduos e seleção de variáveis de acordo com p-valor
fit2<- tirar_variaveis(0, 0, 0, x, y)
fit2[1]
```

```
## [[1]]
##
## z test of coefficients:
##
##               Estimate Std. Error z value Pr(>|z|)
## intercept      0.122436   0.232096   0.5275 0.5978295
## 'Avicultura de Corte' 0.430956   0.133305   3.2328 0.0012256 **
## Pescado         0.309973   0.122283   2.5349 0.0112488 *
## avp12           0.357888   0.071081   5.0350 4.779e-07 ***
## avc5            0.341335   0.128150   2.6636 0.0077320 **
## pes9            -0.441287   0.128116  -3.4444 0.0005722 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

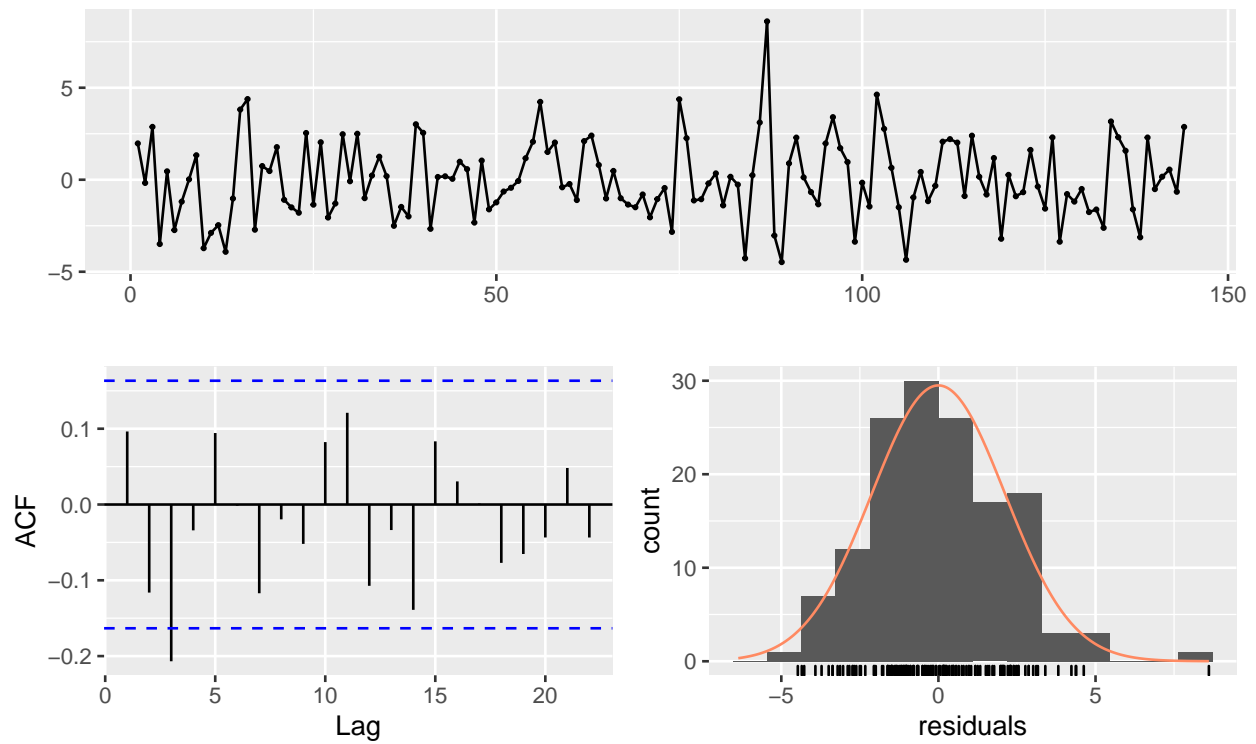
```
xx <- fit2[2]
xx<- xx[[1]]
```

```
fit3 = Arima(y,order=c(0,0,0),xreg=xx)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##               Estimate Std. Error z value Pr(>|z|)
## intercept      0.122436   0.232096   0.5275 0.5978295
## 'Avicultura de Corte' 0.430956   0.133305   3.2328 0.0012256 **
## Pescado         0.309973   0.122283   2.5349 0.0112488 *
## avp12           0.357888   0.071081   5.0350 4.779e-07 ***
## avc5            0.341335   0.128150   2.6636 0.0077320 **
## pes9            -0.441287   0.128116  -3.4444 0.0005722 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

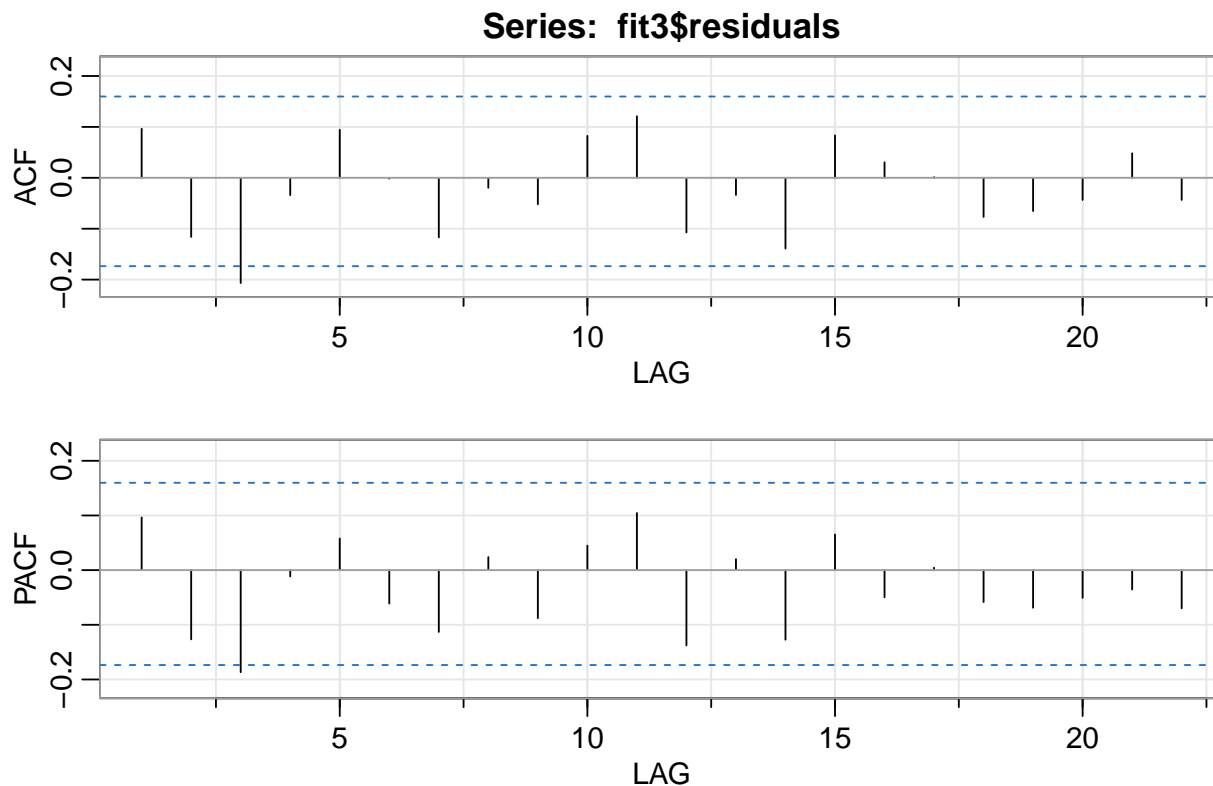
```
checkresiduals(fit3)
```

Residuals from Regression with ARIMA(0,0,0) errors



```
##  
##  Ljung-Box test  
##  
## data:  Residuals from Regression with ARIMA(0,0,0) errors  
## Q* = 14.912, df = 4, p-value = 0.004888  
##  
## Model df: 6.    Total lags used: 10
```

```
acf2(fit3$residuals)
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12]
## ACF   0.1 -0.12 -0.21 -0.03 0.09  0.00 -0.12 -0.02 -0.05  0.08  0.12 -0.11
## PACF  0.1 -0.13 -0.19 -0.01 0.06 -0.06 -0.11  0.02 -0.09  0.04  0.10 -0.14
##      [,13] [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## ACF  -0.03 -0.14  0.08  0.03    0 -0.08 -0.07 -0.04  0.05 -0.04
## PACF  0.02 -0.13  0.07 -0.05    0 -0.06 -0.07 -0.05 -0.04 -0.07
```

```
fit4 = Arima(y,order=c(3,0,0),xreg=xx,include.mean = FALSE,fixed=c(0,0,NA,NA,0,NA,NA,NA))
fit4
```

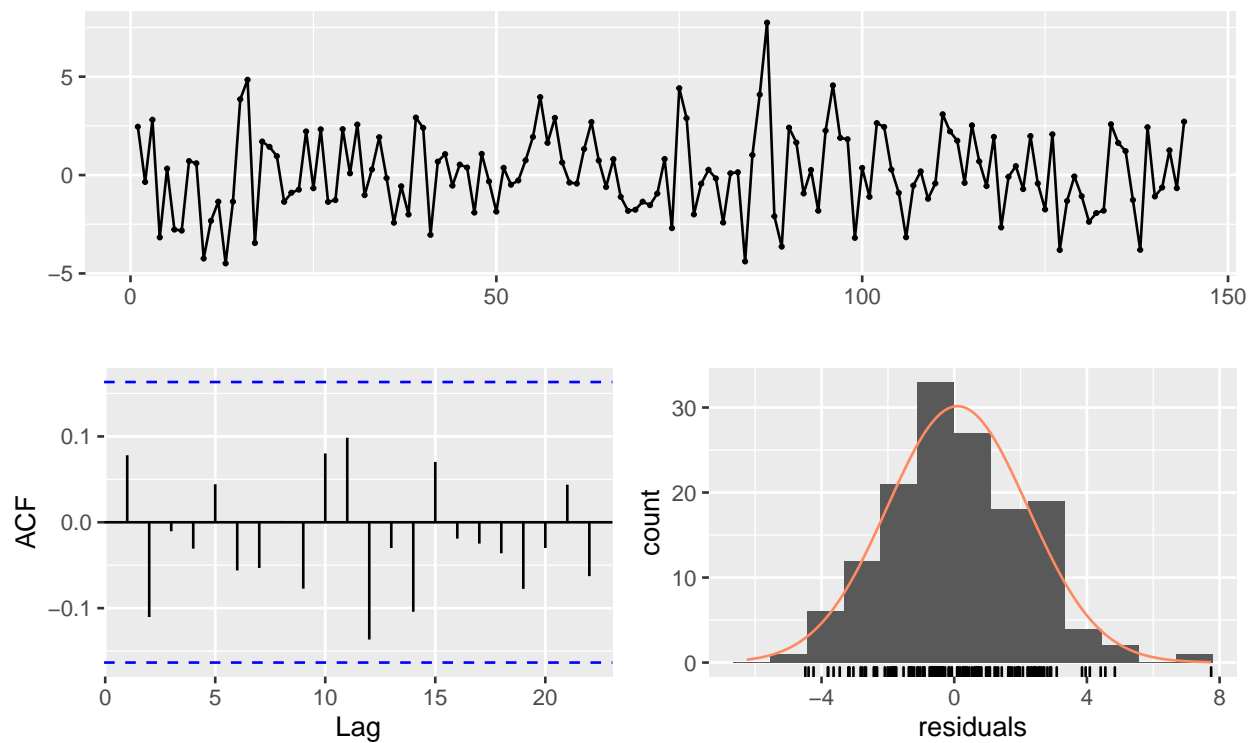
```
## Series: y
## Regression with ARIMA(3,0,0) errors
##
## Coefficients:
##      ar1  ar2      ar3 'Avicultura de Corte'  Pescado  avp12  avc5
##      0    0  -0.2280          0.6010          0  0.4380  0.4151
## s.e.    0    0   0.0826          0.1232          0  0.0624  0.1163
##      pes9
##      -0.3460
## s.e.    0.1074
##
## sigma^2 estimated as 4.628:  log likelihood=-312.18
## AIC=636.35  AICc=636.97  BIC=654.17
```

```
coeftest(fit4)
```

```
##
## z test of coefficients:
##
##           Estimate Std. Error z value Pr(>|z|)
## ar3          -0.227984   0.082567 -2.7612 0.0057588 **
## 'Avicultura de Corte' 0.601047   0.123219  4.8779 1.072e-06 ***
## avp12         0.438035   0.062446  7.0147 2.305e-12 ***
## avc5          0.415126   0.116253  3.5709 0.0003558 ***
## pes9         -0.346032   0.107404 -3.2218 0.0012739 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

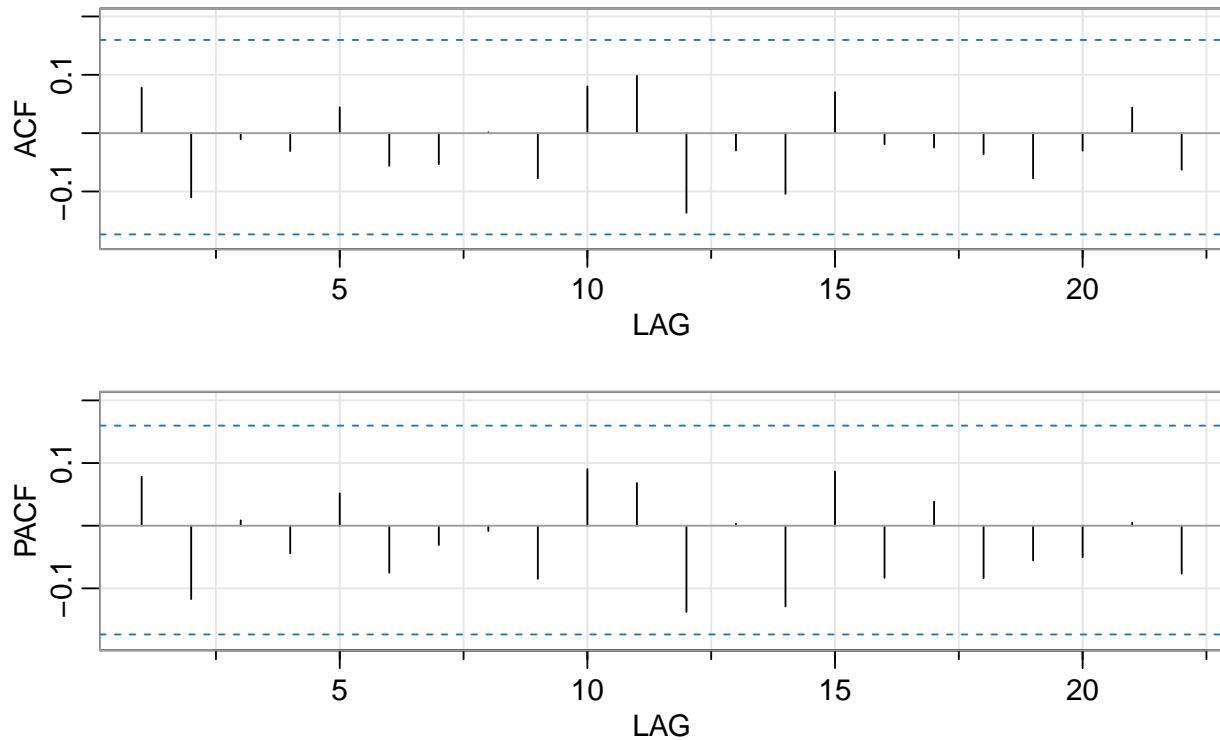
```
checkresiduals(fit4)
```

Residuals from Regression with ARIMA(3,0,0) errors



```
##
## Ljung-Box test
##
## data: Residuals from Regression with ARIMA(3,0,0) errors
## Q* = 7.5364, df = 3, p-value = 0.05663
##
## Model df: 8. Total lags used: 11
```

```
acf2(fit4$residuals, main = "")
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12]
## ACF  0.08 -0.11 -0.01 -0.03  0.04 -0.06 -0.05  0.00 -0.08  0.08  0.10 -0.14
## PACF  0.08 -0.12  0.01 -0.04  0.05 -0.07 -0.03 -0.01 -0.08  0.09  0.07 -0.14
##      [,13] [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## ACF  -0.03 -0.10  0.07 -0.02 -0.02 -0.04 -0.08 -0.03  0.04 -0.06
## PACF  0.00 -0.13  0.09 -0.08  0.04 -0.08 -0.06 -0.05  0.00 -0.08
```

Modelo do Lácteos

Estruturando a base

```
# Estruturando a base

df1<- funcao_lags(data_cut, data_cut$Lácteos, 'lact1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Postura', 'avp1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc6', 6)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov2', 2)
df1 <- funcao_lags(df1, df1$Pescado, 'pes4', 4)
df1 <- funcao_lags(df1, df1$Pescado, 'pes9', 9)

df2 <- na.omit(df1)
```

Separando variável preditora e as covariáveis

```
#Separando variável preditora e as covariáveis
x = model.matrix(Lácteos~.,df2)[-1]
y = df2$Lácteos
```

Regressão classifica no contexto de Séries Temporais

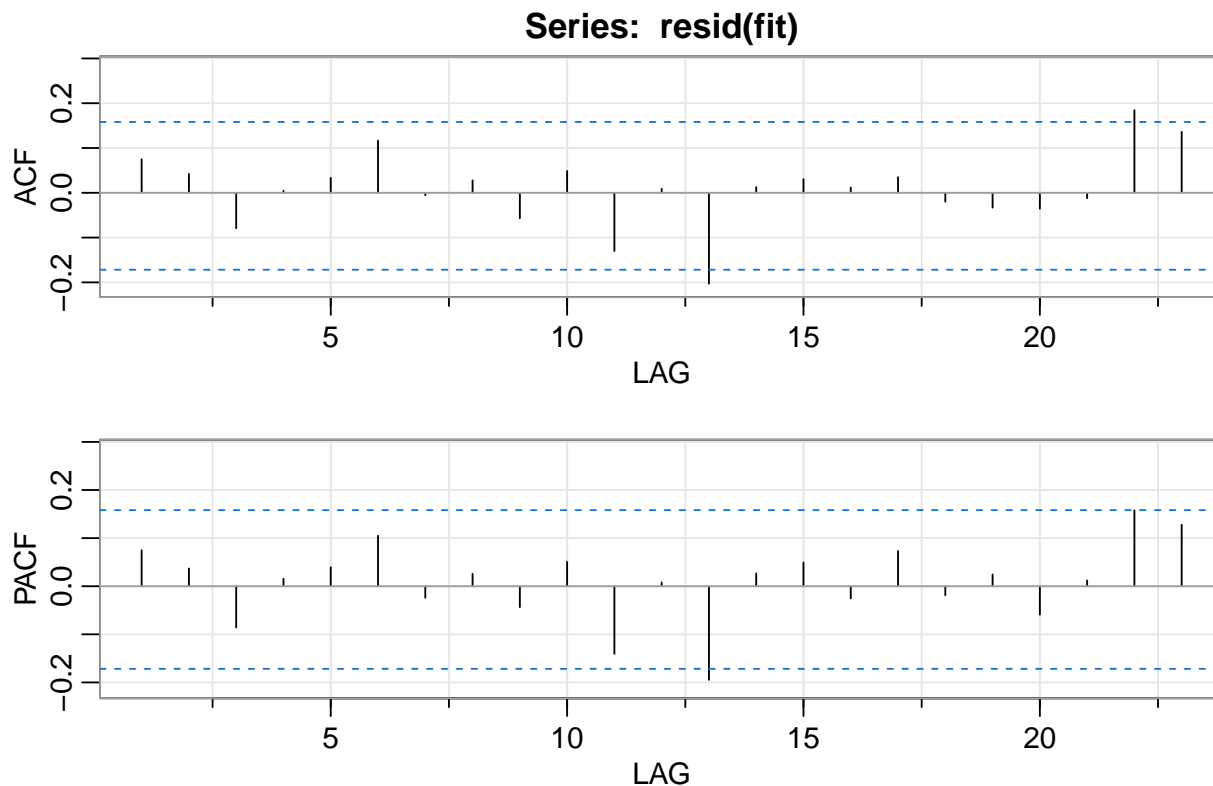
Criando o modelo de Regressão Simples

```
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.9889 -0.5093 -0.0365  0.3740  3.7350
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.15734    0.11576   1.359   0.1763
## xBovinocultura    -0.03768    0.04196  -0.898   0.3707
## x'Avicultura de Corte' 0.13320    0.06205   2.147   0.0336 *
## x'Avicultura de Postura' 0.03863    0.03119   1.238   0.2177
## xPescado          -0.03187    0.05250  -0.607   0.5449
## xSuinocultura      -0.01598    0.11157  -0.143   0.8863
## xlact1             0.58502    0.06341   9.225 5.09e-16 ***
## xavp1              0.03060    0.03009   1.017   0.3110
## xavc6              0.07371    0.05424   1.359   0.1765
## xbov2              -0.07026    0.04512  -1.557   0.1217
## xpes4              0.08919    0.05472   1.630   0.1055
## xpes9             -0.09059    0.05370  -1.687   0.0939 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8391 on 135 degrees of freedom
## Multiple R-squared:  0.5426, Adjusted R-squared:  0.5053
## F-statistic: 14.56 on 11 and 135 DF, p-value: < 2.2e-16
```

Análise dos Resíduos

```
# Análise dos Resíduos
acf2(resid(fit))
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.07 0.04 -0.08 0.00 0.03 0.12 -0.01 0.03 -0.06 0.05 -0.13 0.01 -0.20
## PACF 0.07 0.04 -0.09 0.02 0.04 0.10 -0.02 0.03 -0.04 0.05 -0.14 0.01 -0.19
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF   0.01 0.03 0.01 0.03 -0.02 -0.03 -0.04 -0.01 0.18 0.14
## PACF  0.03 0.05 -0.03 0.07 -0.02 0.02 -0.06 0.01 0.16 0.13
```

Análise dos resíduos e seleção de variáveis de acordo com p-valor

```
# Análise dos resíduos e seleção de variáveis de acordo com p-valor
fit2 <- tirar_variaveis(0, 0, 0, x, y)

fit2[1]
```

```
## [[1]]
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## intercept  0.036024   0.080495  0.4475 0.654489
## lact1      0.604999   0.060150 10.0582 < 2.2e-16 ***
## avc6       0.107164   0.049809  2.1515 0.031436 *
## pes4       0.145117   0.046861  3.0968 0.001956 **
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

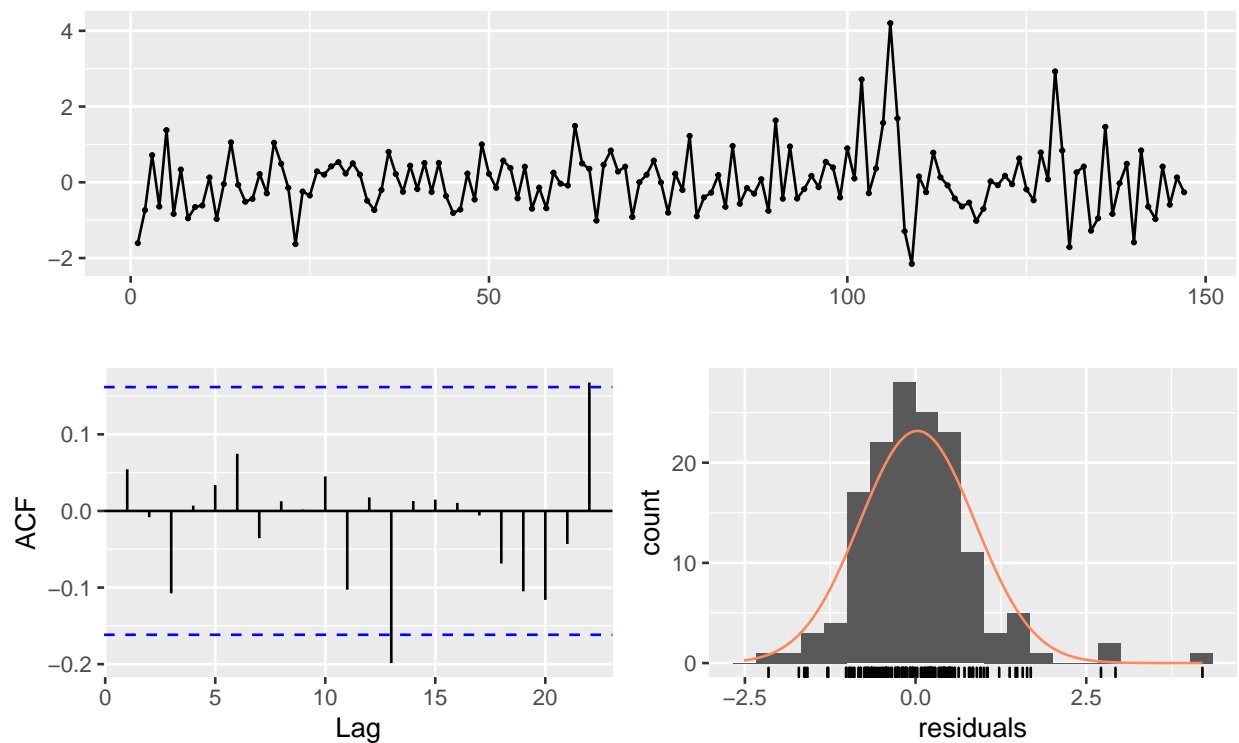
```
xx <- fit2[2]
xx<- xx[[1]]
```

```
fit3 = Arima(y,order=c(0,0,0),xreg=xx,include.mean = FALSE)
coeftest(fit3)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## lact1 0.611972   0.058137 10.5265 < 2.2e-16 ***
## avc6  0.112091   0.048610  2.3059 0.0211138 *
## pes4  0.150462   0.045344  3.3182 0.0009059 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
checkresiduals(fit3)
```

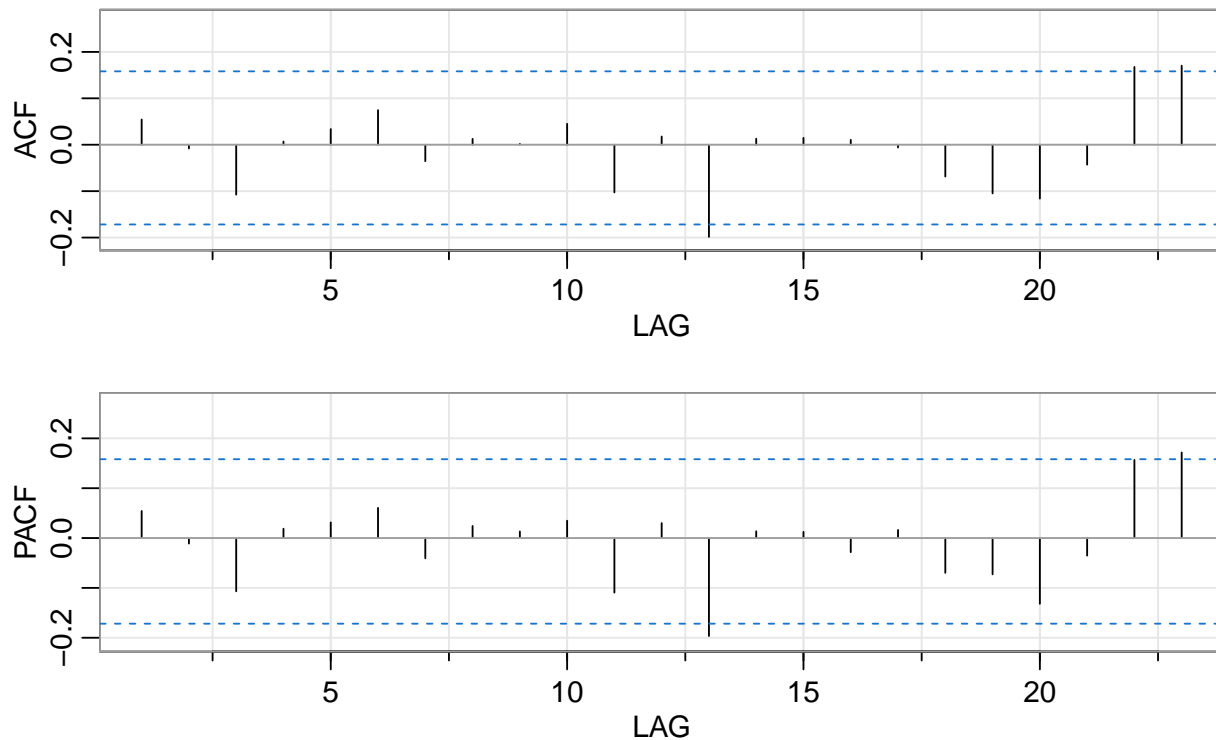
Residuals from Regression with ARIMA(0,0,0) errors



```
##
## Ljung-Box test
```

```
##
## data: Residuals from Regression with ARIMA(0,0,0) errors
## Q* = 3.8077, df = 7, p-value = 0.8016
##
## Model df: 3. Total lags used: 10
```

```
acf2(fit3$residuals, main = "")
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.05 -0.01 -0.11  0.01  0.03  0.07 -0.04  0.01  0.00  0.05 -0.10  0.02 -0.2
## PACF  0.05 -0.01 -0.11  0.02  0.03  0.06 -0.04  0.02  0.01  0.03 -0.11  0.03 -0.2
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF   0.01  0.01  0.01 -0.01 -0.07 -0.10 -0.12 -0.04  0.17  0.17
## PACF   0.01  0.01 -0.03  0.02 -0.07 -0.07 -0.13 -0.04  0.16  0.17
```

Modelo do Suinocultura

Estruturando a base

```
# Estruturando a base
df1<- funcao_lags(data_cut, data_cut$Suinocultura, 'su1', 1)
```

```
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc6', 6)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc10', 10)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov1', 1)
df2 <- na.omit(df1)
```

Separando variável preditora e as covariáveis

```
# Separando variável preditora e as covariáveis
x = model.matrix(Suinocultura~.,df2)[-1]
y = df2$Suinocultura
```

Regressão classifica no contexto de Séries Temporais

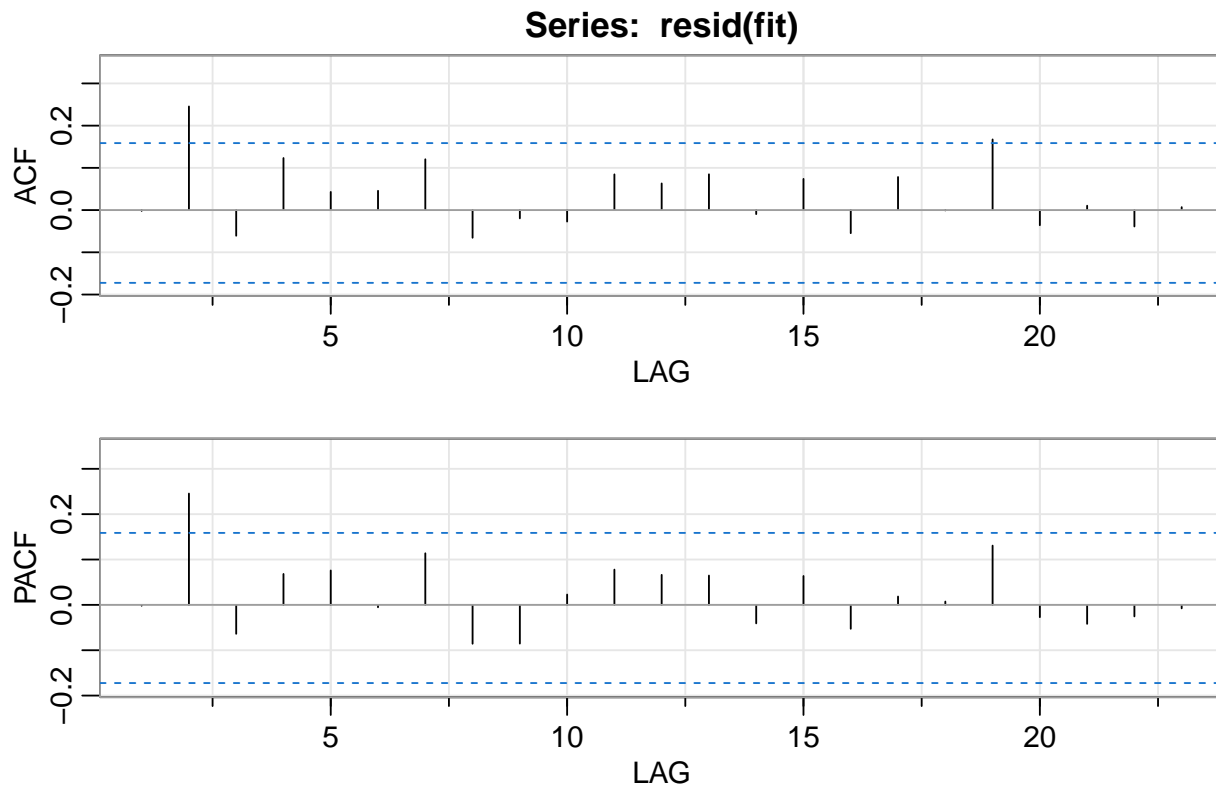
Criando o modelo de Regressão Simples

```
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.41583 -0.39128 -0.06148  0.35167  1.67796
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.1920512   0.0735974   2.609  0.01009 *
## xBovinocultura  0.0804015   0.0323240   2.487  0.01409 *
## x'Avicultura de Corte' 0.0242656   0.0481760   0.504  0.61530
## x'Avicultura de Postura' 0.0098311   0.0211227   0.465  0.64237
## xPescado      -0.0008281   0.0373895  -0.022  0.98236
## xLácteos       0.0338683   0.0463772   0.730  0.46649
## xsu1           0.2273228   0.0776042   2.929  0.00399 **
## xavc1           0.0865616   0.0462072   1.873  0.06318 .
## xavc6          -0.0686232   0.0384825  -1.783  0.07680 .
## xavc10          0.0625848   0.0364282   1.718  0.08808 .
## xbov1           0.0738746   0.0405940   1.820  0.07100 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6066 on 135 degrees of freedom
## Multiple R-squared:  0.3972, Adjusted R-squared:  0.3526
## F-statistic: 8.896 on 10 and 135 DF,  p-value: 3.949e-11
```

Análise dos Resíduos


```
# Análise dos Resíduos
acf2(resid(fit))
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF    0 0.25 -0.06 0.12 0.04  0.05 0.12 -0.07 -0.02 -0.03  0.08  0.06  0.08
## PACF    0 0.25 -0.06 0.07 0.08 -0.01 0.11 -0.09 -0.09  0.02  0.08  0.07  0.06
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF -0.01  0.07 -0.05  0.08  0.00  0.17 -0.04  0.01 -0.04  0.01
## PACF -0.04  0.06 -0.05  0.02  0.01  0.13 -0.03 -0.04 -0.03 -0.01
```

Análise dos resíduos e seleção de variáveis de acordo com p-valor

```
# Análise dos resíduos e seleção de variáveis de acordo com p-valor

fit2 <- tirar_variaveis(0, 0, 0, x, y)

fit2[1]
```

```
## [[1]]
##
## z test of coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## intercept    0.196715   0.062298  3.1576 0.0015905 **
```

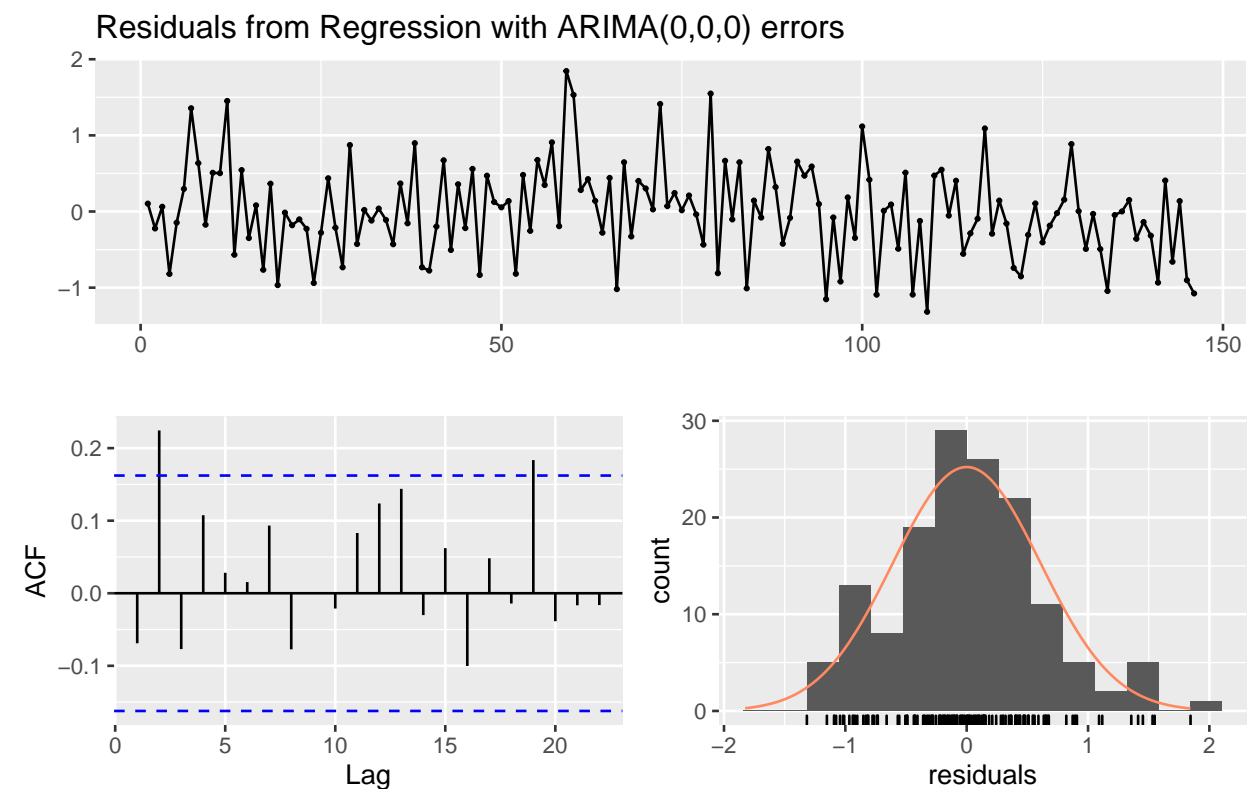
```
## Bovinocultura 0.110931 0.024454 4.5363 5.725e-06 ***
## su1          0.293553 0.073307 4.0044 6.217e-05 ***
## avc1         0.134372 0.038667 3.4751 0.0005106 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
xx <- fit2[2]
xx<- xx[[1]]
```

```
fit3 = Arima(y,order=c(0,0,0),xreg=xx)
coeftest(fit3)
```

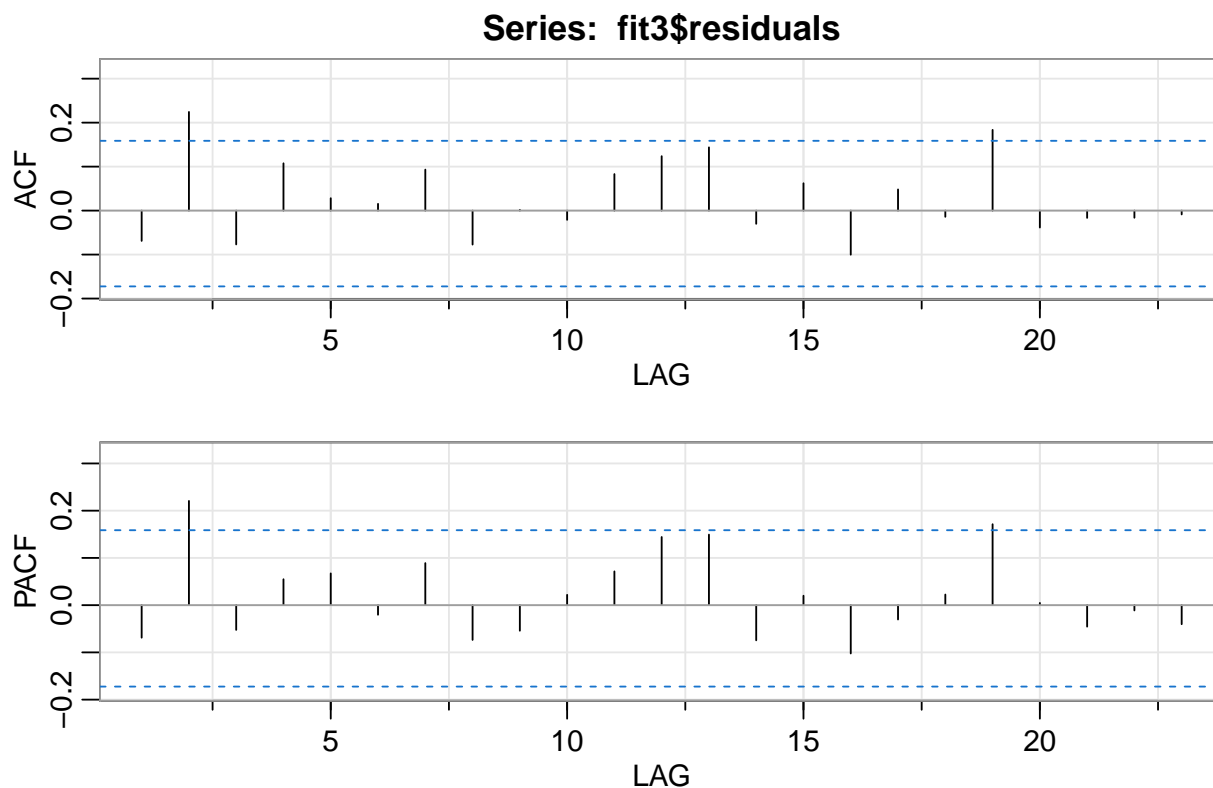
```
##
## z test of coefficients:
##
##          Estimate Std. Error z value Pr(>|z|)
## intercept    0.196715   0.062298   3.1576 0.0015905 **
## Bovinocultura 0.110931   0.024454   4.5363 5.725e-06 ***
## su1           0.293553   0.073307   4.0044 6.217e-05 ***
## avc1          0.134372   0.038667   3.4751 0.0005106 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
checkresiduals(fit3)
```



```
##
## Ljung-Box test
##
## data: Residuals from Regression with ARIMA(0,0,0) errors
## Q* = 13.432, df = 6, p-value = 0.03667
##
## Model df: 4. Total lags used: 10
```

```
acf2(fit3$residuals)
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF -0.07 0.22 -0.08 0.11 0.03 0.02 0.09 -0.08 0.00 -0.02 0.08 0.12 0.14
## PACF -0.07 0.22 -0.05 0.05 0.07 -0.02 0.09 -0.07 -0.05 0.02 0.07 0.14 0.15
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF -0.03 0.06 -0.1 0.05 -0.01 0.18 -0.04 -0.02 -0.02 -0.01
## PACF -0.07 0.02 -0.1 -0.03 0.02 0.17 0.00 -0.05 -0.01 -0.04
```

```
fit4 = Arima(y,order=c(2,0,0),xreg=xx,fixed =c(0,NA,NA,NA,NA,NA))
fit4
```

```
## Series: y
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
```

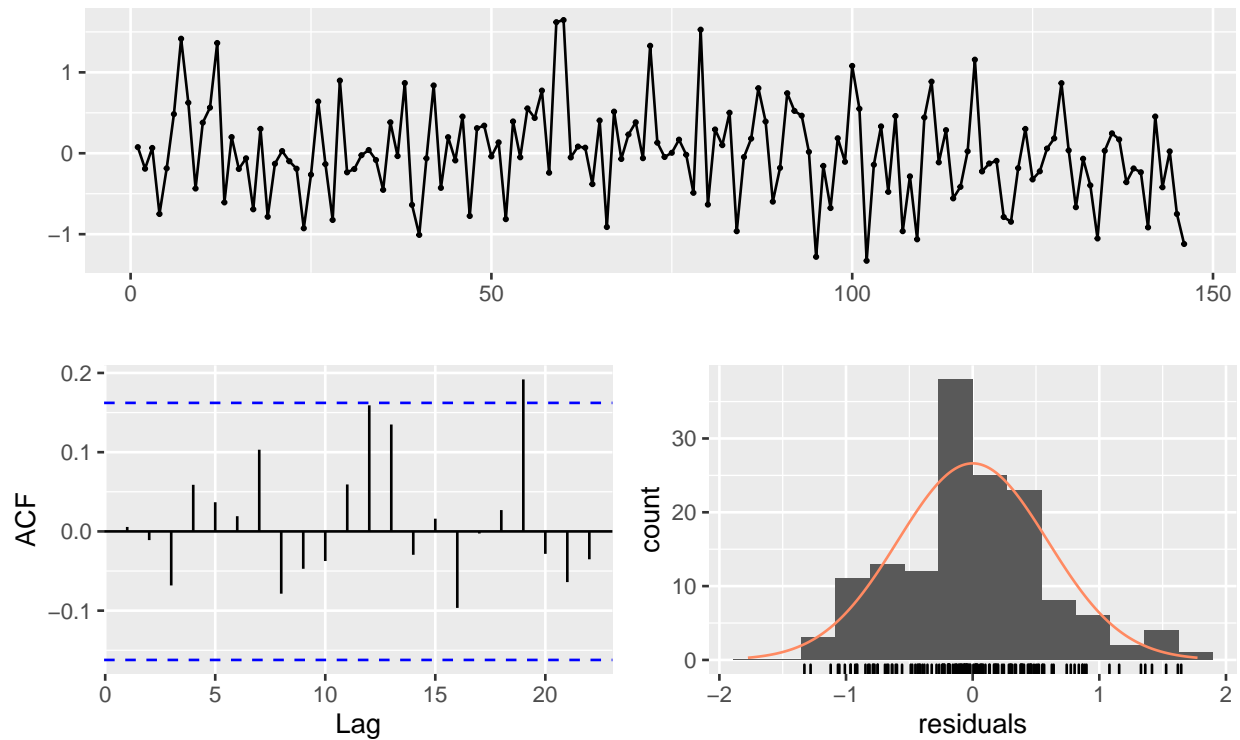
```
##          ar1      ar2  intercept  Bovinocultura      su1      avc1
##          0  0.2407      0.2107      0.1116  0.2485  0.1412
## s.e.      0  0.0832      0.0750      0.0235  0.0747  0.0370
##
## sigma^2 estimated as 0.36:  log likelihood=-130.1
## AIC=272.2   AICc=272.81   BIC=290.11
```

```
coeftest(fit4)
```

```
##
## z test of coefficients:
##
##          Estimate Std. Error z value  Pr(>|z|)
## ar2          0.240708   0.083246   2.8915 0.0038338 **
## intercept     0.210659   0.075006   2.8086 0.0049764 **
## Bovinocultura  0.111554   0.023545   4.7379 2.159e-06 ***
## su1           0.248548   0.074714   3.3267 0.0008789 ***
## avc1          0.141187   0.037044   3.8113 0.0001382 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
checkresiduals(fit4)
```

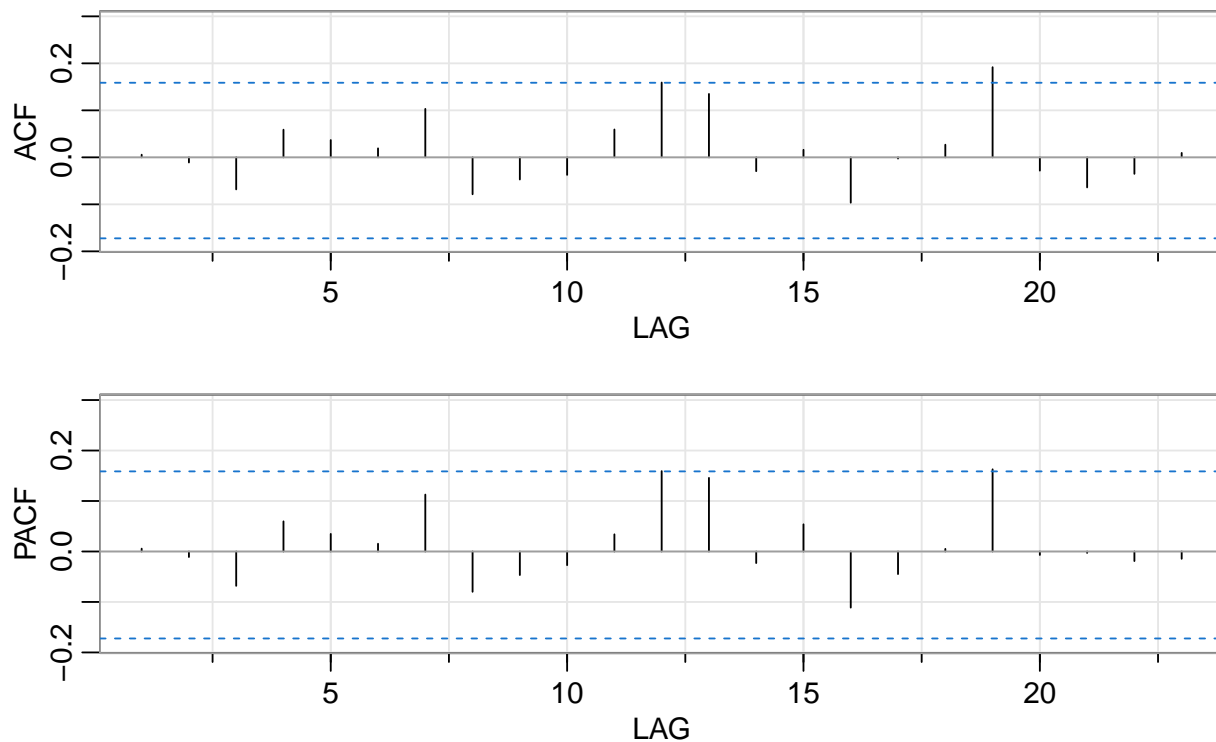
Residuals from Regression with ARIMA(2,0,0) errors



```
##
```

```
## Ljung-Box test
##
## data: Residuals from Regression with ARIMA(2,0,0) errors
## Q* = 4.7092, df = 4, p-value = 0.3185
##
## Model df: 6. Total lags used: 10
```

```
acf2(fit4$residuals, main = "")
```



```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## ACF  0.01 -0.01 -0.07 0.06 0.04 0.02 0.10 -0.08 -0.05 -0.04 0.06 0.16 0.13
## PACF  0.01 -0.01 -0.07 0.06 0.03 0.02 0.11 -0.08 -0.05 -0.03 0.03 0.16 0.15
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23]
## ACF -0.03 0.02 -0.10 0.00 0.03 0.19 -0.03 -0.06 -0.04 0.01
## PACF -0.02 0.05 -0.11 -0.04 0.01 0.16 -0.01 0.00 -0.02 -0.01
```

Análise das séries temporais anuais

Análise Descritiva

```
# Análise das séries temporais anuais
head(data_anual)
```

```
## # A tibble: 6 x 7
##   Anos 'Avicultura de ~ 'Avicultura Pos~ 'Bovinocultura ~ Lácteos Pescado
##   <dbl>         <dbl>         <dbl>         <dbl> <dbl> <dbl>
## 1 2007          12.3          26.0          20.5  21.7  1.40
## 2 2008           8.33           8.27          23.7  -2.41  9.89
## 3 2009          -1.25           3.77          -3.75   4.55  7.12
## 4 2010           9.27           5.48          25.9   4.36  8.02
## 5 2011           6.21           9.15           3.67   7.51  6.61
## 6 2012          11.2          18.8           0.792   7.76  14.2
## # ... with 1 more variable: Suinocultura <dbl>
```

Análise Descritiva

```
z_avc = data_anual$'Avicultura de Corte'
z_avc = ts(z_avc)
```

```
z_avp = data_anual$'Avicultura Postura'
z_avp = ts(z_avp)
```

```
z_bov = data_anual$'Bovinocultura de corte'
z_bov = ts(z_bov)
```

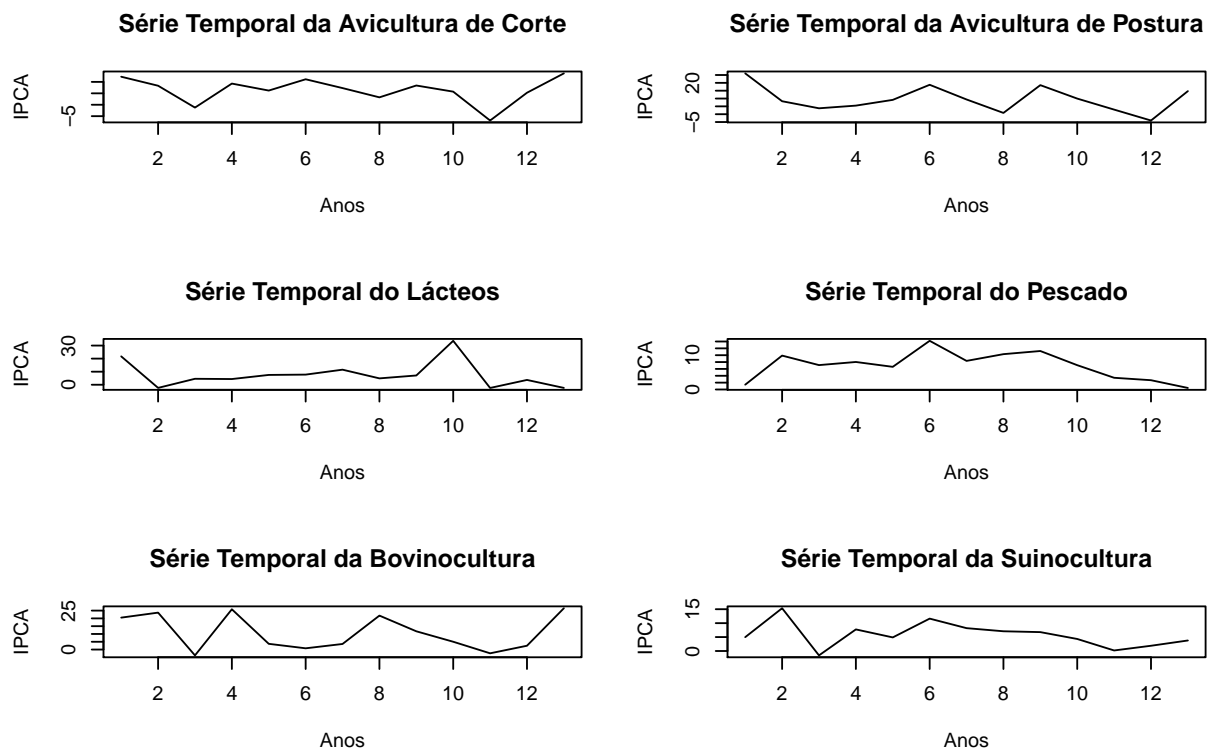
```
z_lac = data_anual$'Lácteos'
z_lac = ts(z_lac)
```

```
z_pesc = data_anual$Pescado
z_pesc = ts(z_pesc)
```

```
z_suino = data_anual$Suinocultura
z_suino = ts(z_suino)
```

Análise Descritiva

```
par(mfrow = c(3,2))
plot(z_avc,main="Série Temporal da Avicultura de Corte", xlab= "Anos", ylab="IPCA")
plot(z_avp,main="Série Temporal da Avicultura de Postura", xlab= "Anos", ylab="IPCA")
plot(z_lac,main="Série Temporal do Lácteos", xlab= "Anos", ylab="IPCA")
plot(z_pesc,main="Série Temporal do Pescado", xlab= "Anos", ylab="IPCA")
plot(z_bov,main="Série Temporal da Bovinocultura", xlab= "Anos", ylab="IPCA")
plot(z_suino,main="Série Temporal da Suinocultura", xlab= "Anos", ylab="IPCA")
```



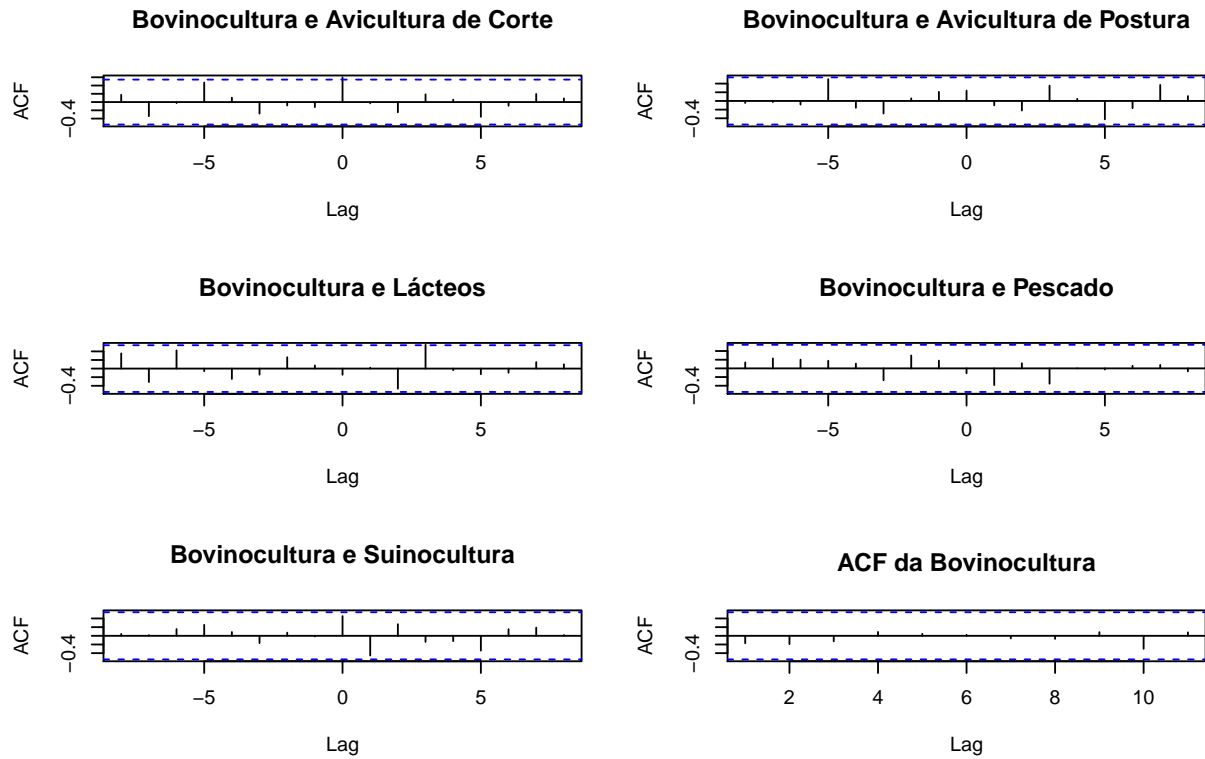
Definindo variáveis do modelo

```
# Variáveis do modelo
library(glmnet)

colnames(data_anual) = c("ANO", "AVC", "AVP", "BOV", "LAC", "PESC", "SUIN")
data_anual = data_anual[, -1]
```

Regressão Lasso para Bovinocultura

```
#Correlações cruzadas da Bovinocultura
par(mfrow = c(3,2))
ccf(z_bov, z_avc, main="Bovinocultura e Avicultura de Corte")
ccf(z_bov, z_avp, main="Bovinocultura e Avicultura de Postura")
ccf(z_bov, z_lac, main="Bovinocultura e Látceos")
ccf(z_bov, z_pesc, main="Bovinocultura e Pescado")
ccf(z_bov, z_suino, main="Bovinocultura e Suinocultura")
acf(z_bov, main = "ACF da Bovinocultura")
```

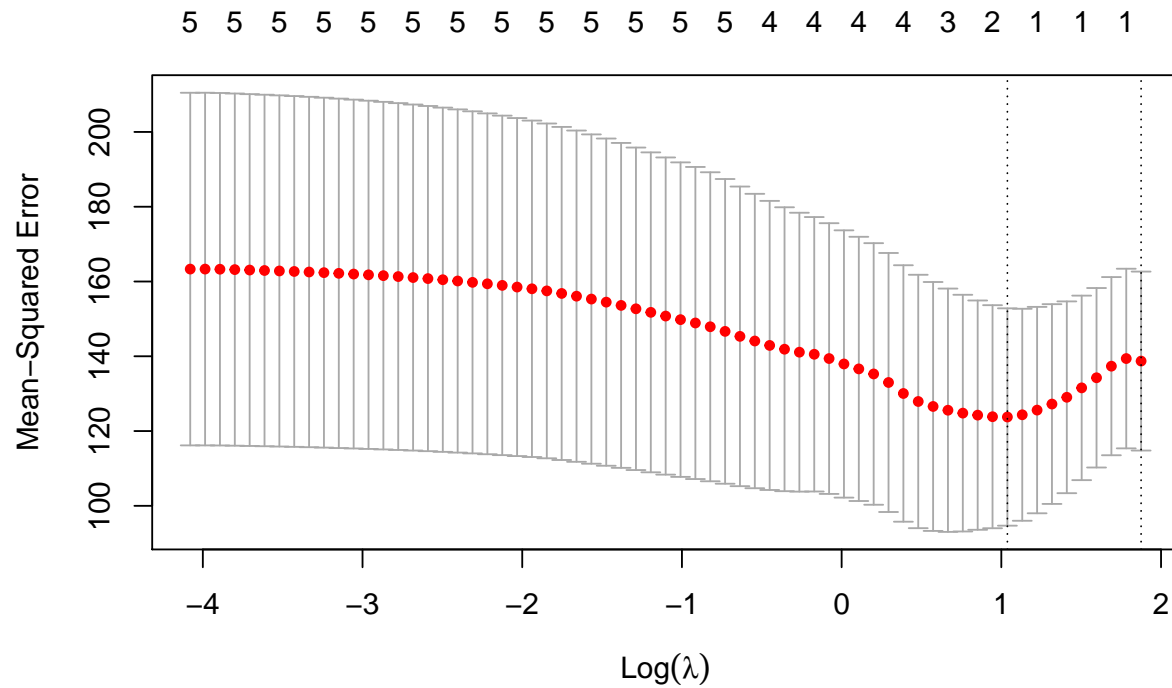


```
# Regressão LASSO
x = model.matrix(BOV~ .,data=data_anual)[,-1]
y = data_anual$BOV

cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
```

```
##
## Call: cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min  2.823    10  123.8 29.07         2
## 1se  6.522     1  138.7 23.93         0
```

```
par(mfrow=c(1,1))
plot(cv.model)
```

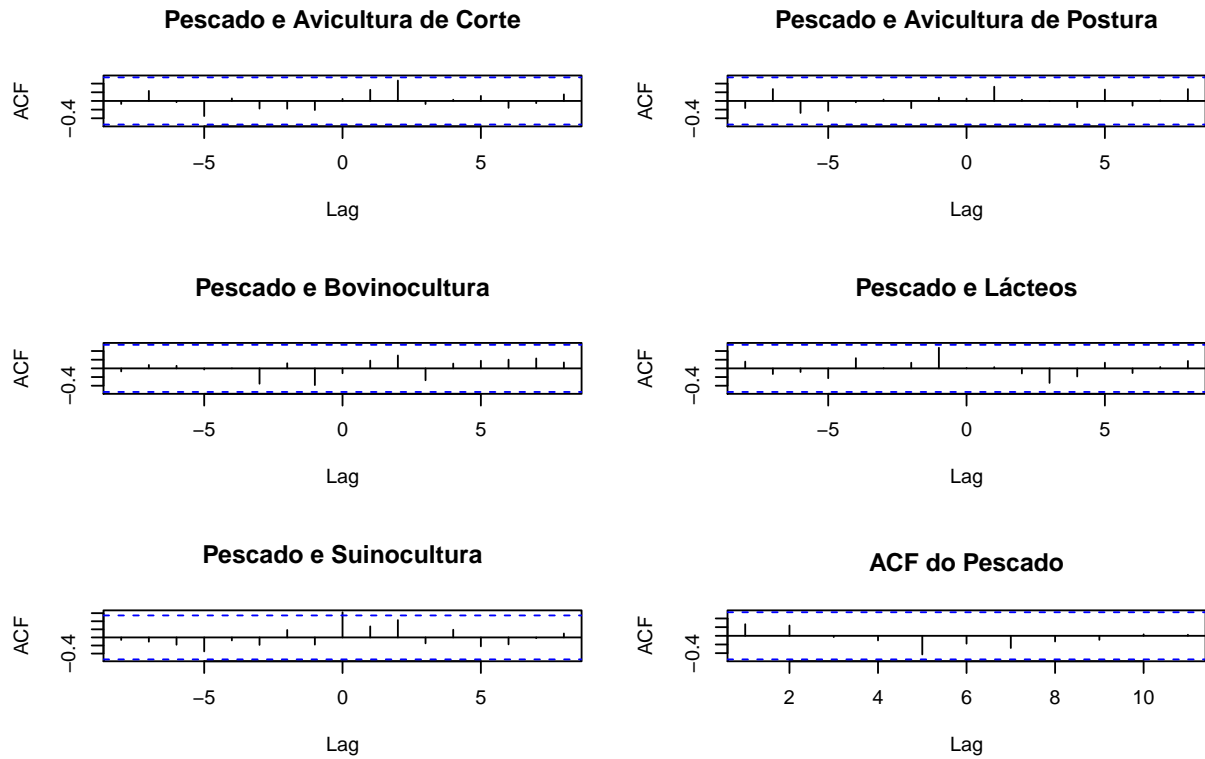
```
coef(cv.model,cv.model$lambda.min)
```

```
## 6 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 6.24941948
## AVC         0.67510339
## AVP         .
## LAC         .
## PESC        .
## SUIN        0.03047208
```

Regressão Lasso para o Pescado

```
# Pescados

par(mfrow = c(3,2))
ccf(z_pesc,z_avc,main="Pescado e Avicultura de Corte")
ccf(z_pesc,z_avp,main="Pescado e Avicultura de Postura")
ccf(z_pesc,z_bov,main="Pescado e Bovinocultura")
ccf(z_pesc,z_lac,main="Pescado e Lâcteos")
ccf(z_pesc,z_suino,main="Pescado e Suinocultura")
acf(z_pesc, main = "ACF do Pescado")
```

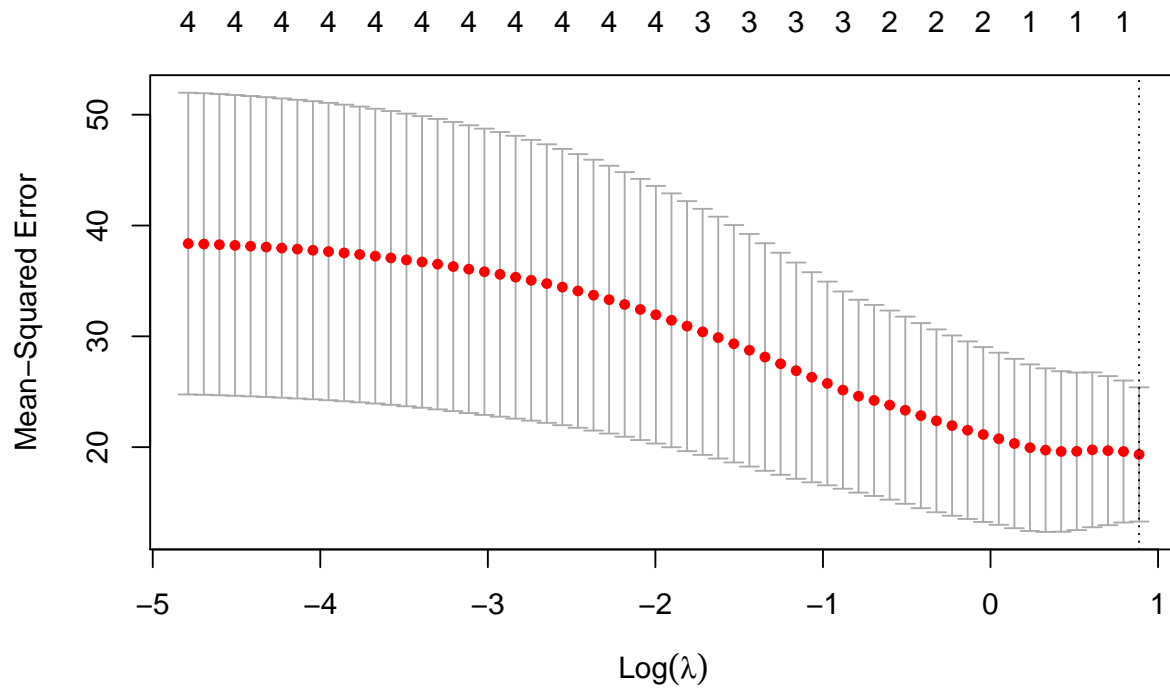


```
# Regressão Lasso
x = model.matrix(PESC~ .,data=data_anual)[,-1]
y = data_anual$PESC

cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
```

```
##
## Call:  cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min  2.427      1   19.34 6.057         0
## 1se  2.427      1   19.34 6.057         0
```

```
par(mfrow=c(1,1))
plot(cv.model)
```



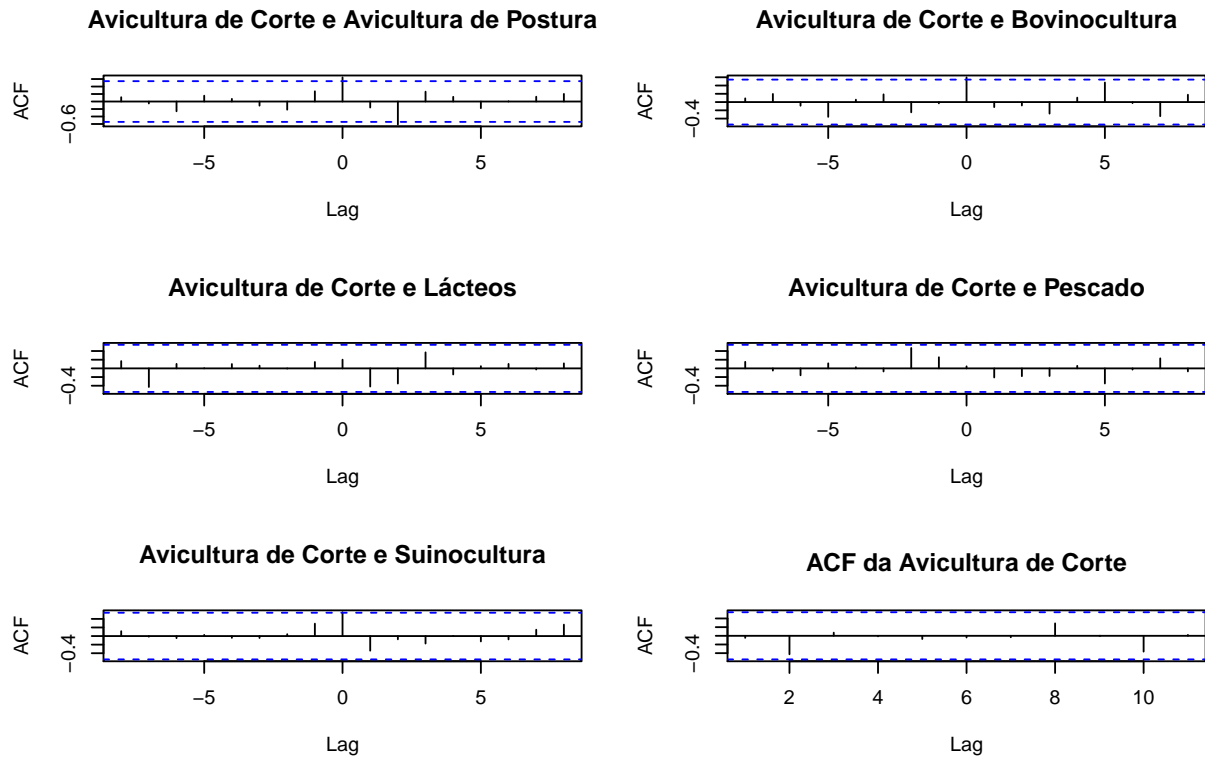
```
coef(cv.model,cv.model$lambda.min)
```

```
## 6 x 1 sparse Matrix of class "dgCMatrix"
##           1
## (Intercept) 6.982923
## AVC          .
## AVP           .
## BOV           .
## LAC           .
## SUIN          .
```

Regressão Lasso para a Avicultura de Corte

```
# Avicultura de Corte

par(mfrow = c(3,2))
ccf(z_avc,z_avp,main="Avicultura de Corte e Avicultura de Postura")
ccf(z_avc,z_bov,main="Avicultura de Corte e Bovinocultura")
ccf(z_avc,z_lac,main="Avicultura de Corte e Lácteos")
ccf(z_avc,z_pesc,main="Avicultura de Corte e Pescado")
ccf(z_avc,z_suino,main="Avicultura de Corte e Suinocultura")
acf(z_avc, main = "ACF da Avicultura de Corte")
```



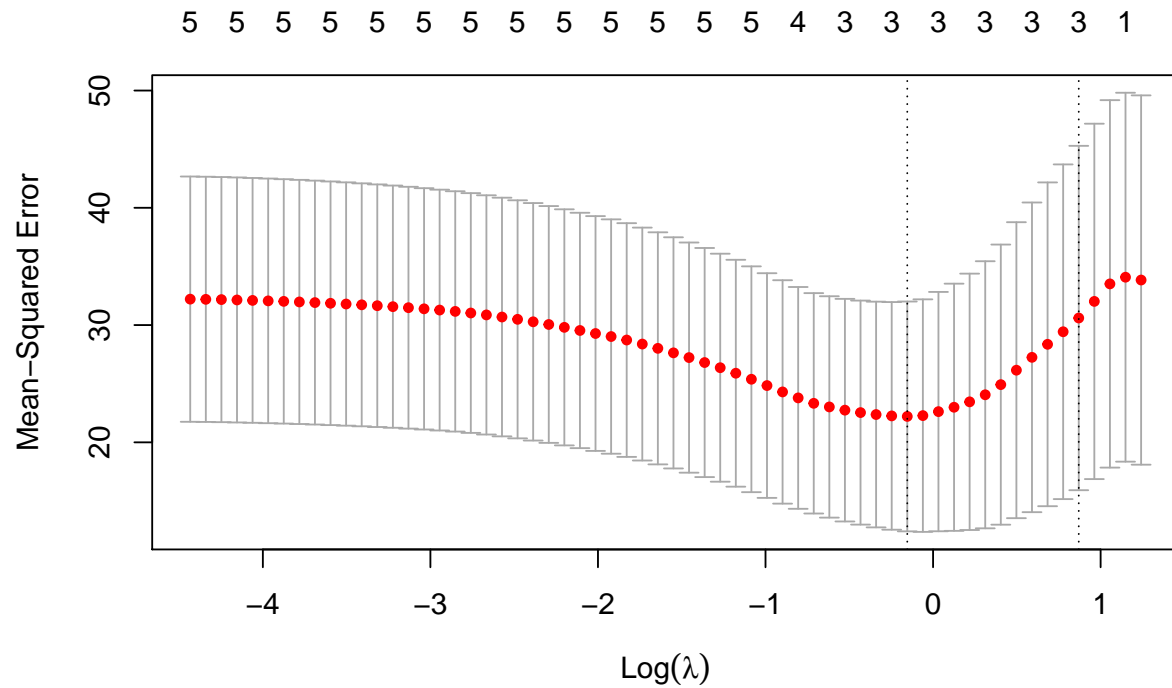
```
## Regressão Lasso
```

```
x = model.matrix(AVC~ .,data=data_anual)[,-1]
y = data_anual$AVC
```

```
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
```

```
##
## Call: cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min 0.8574    16   22.21  9.799         3
## 1se 2.3857     5   30.60 14.683         3
```

```
par(mfrow=c(1,1))
plot(cv.model)
```



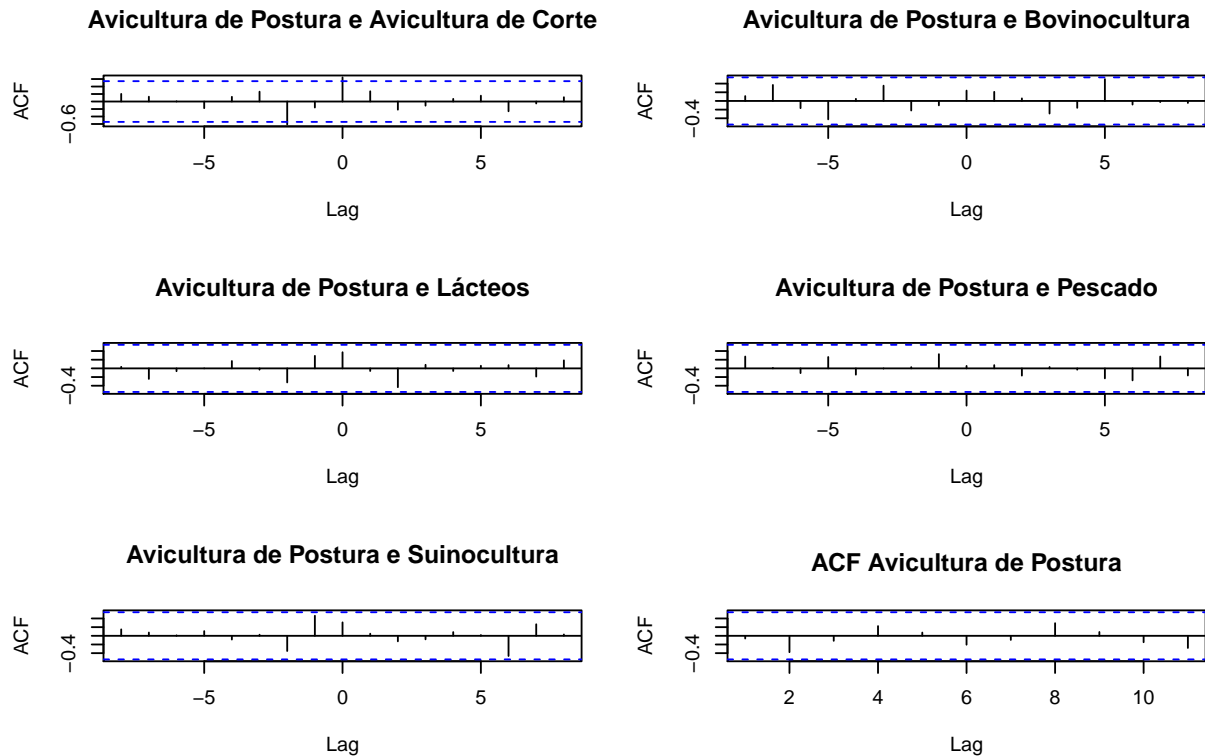
```
coef(cv.model,cv.model$lambda.min)
```

```
## 6 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 1.4126810
## AVP         0.2502444
## BOV         0.1374334
## LAC         .
## PESC        .
## SUIN        0.1894346
```

Regressão Lasso para Avicultura de Postura

```
# Avicultura de Postura
```

```
par(mfrow = c(3,2))
ccf(z_avp,z_avc,main="Avicultura de Postura e Avicultura de Corte")
ccf(z_avp,z_bov,main="Avicultura de Postura e Bovinocultura")
ccf(z_avp,z_lac,main="Avicultura de Postura e L cteos")
ccf(z_avp,z_pesc,main="Avicultura de Postura e Pescado")
ccf(z_avp,z_suino,main="Avicultura de Postura e Suinocultura")
acf(z_avp, main = "ACF Avicultura de Postura")
```

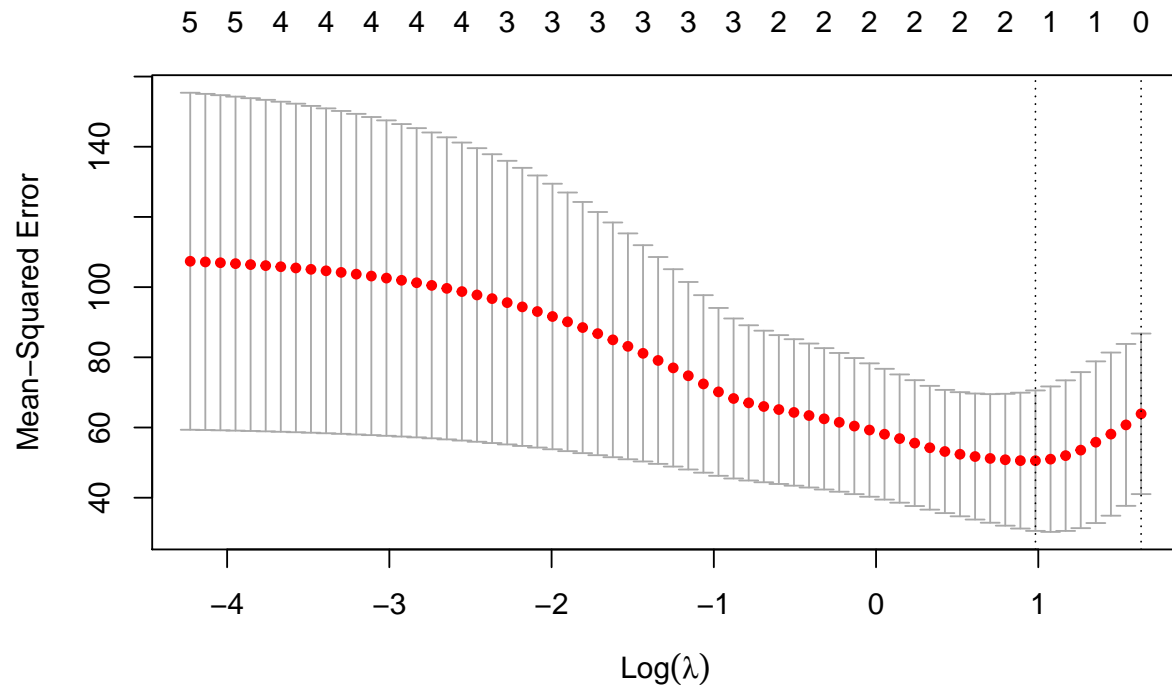


```
# Regressão Lasso
x = model.matrix(AVP~ .,data=data_anual)[,-1]
y = data_anual$AVP
```

```
par(mfrow=c(1,1))
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
```

```
##
## Call: cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min  2.671      8  50.55 20.01         1
## 1se  5.123      1  63.90 22.87         0
```

```
plot(cv.model)
```

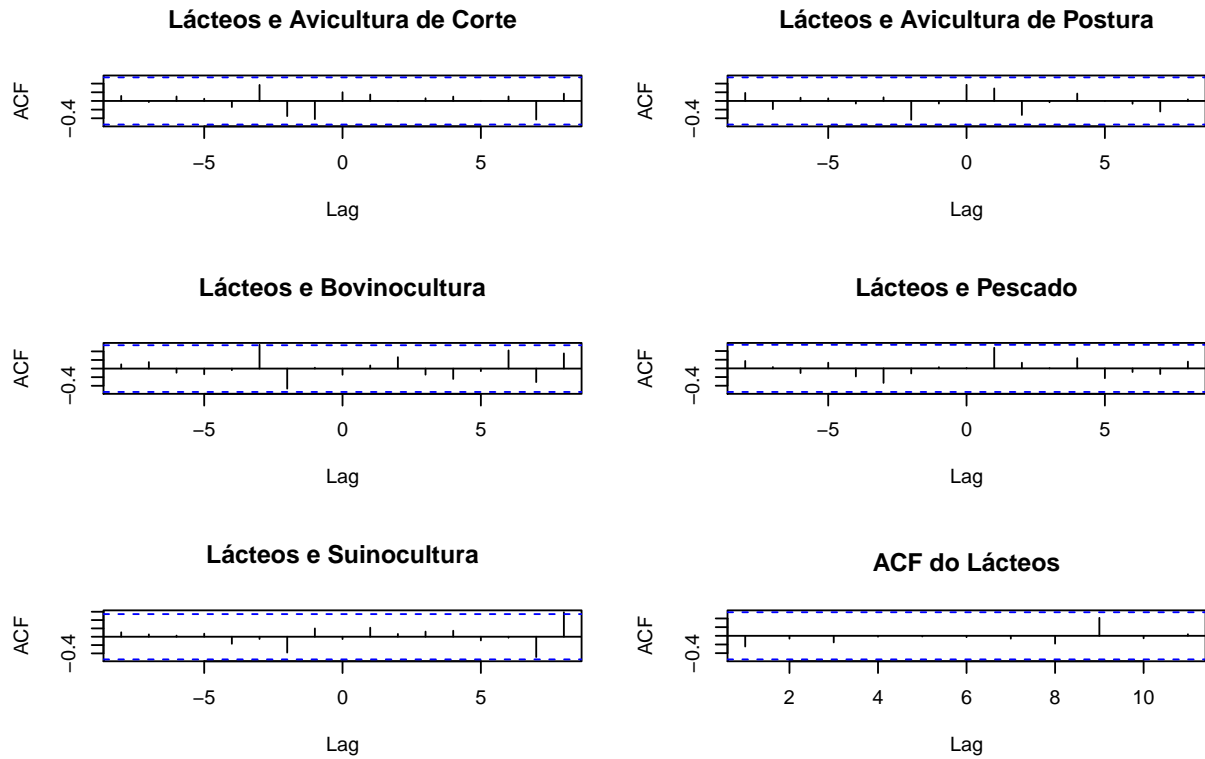


```
coef(cv.model, cv.model$lambda.min)
```

```
## 6 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 6.6205901
## AVC         0.4565669
## BOV         .
## LAC         .
## PESC        .
## SUIN        .
```

Regressão Lasso para o Lácteos

```
# Lácteos
par(mfrow = c(3,2))
ccf(z_lac, z_avc, main="Lácteos e Avicultura de Corte")
ccf(z_lac, z_avp, main="Lácteos e Avicultura de Postura")
ccf(z_lac, z_bov, main="Lácteos e Bovinocultura")
ccf(z_lac, z_pesc, main="Lácteos e Pescado")
ccf(z_lac, z_suino, main="Lácteos e Suinocultura")
acf(z_lac, main = "ACF do Lácteos")
```

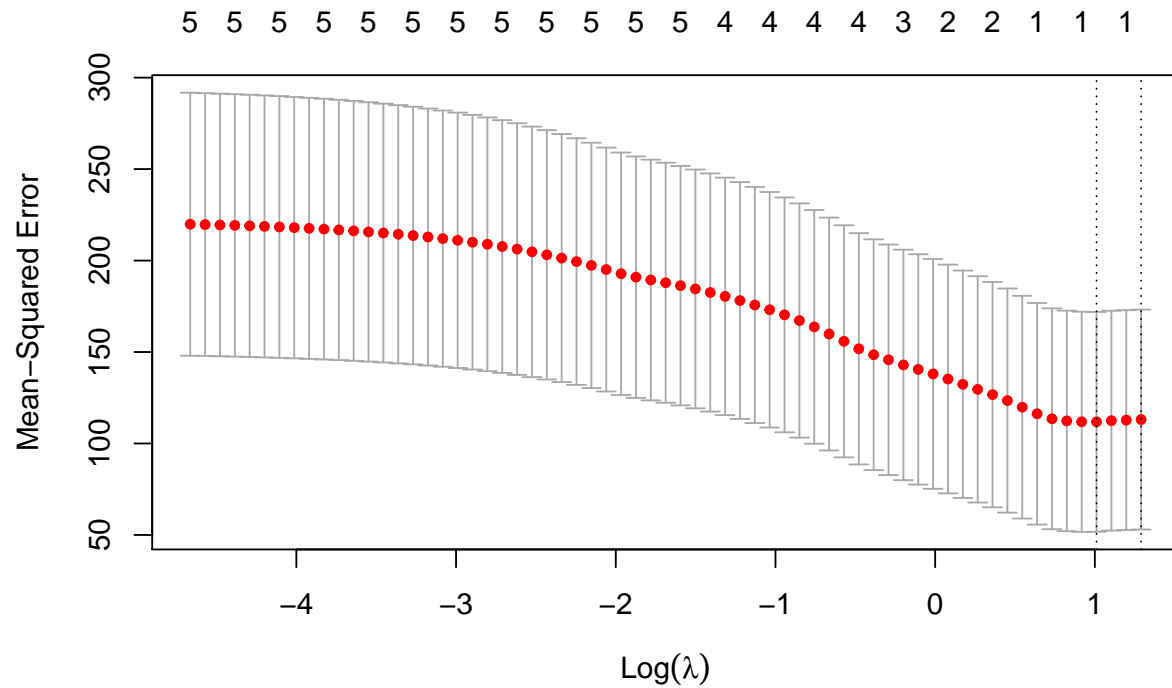


```
# Regressão Lasso
x = model.matrix(LAC~ .,data=data_anual)[,-1]
y = data_anual$LAC
```

```
par(mfrow=c(1,1))
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
```

```
##
## Call: cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure   SE Nonzero
## min  2.747     4   111.8 60.1         1
## 1se  3.631     1   113.1 60.1         0
```

```
plot(cv.model)
```

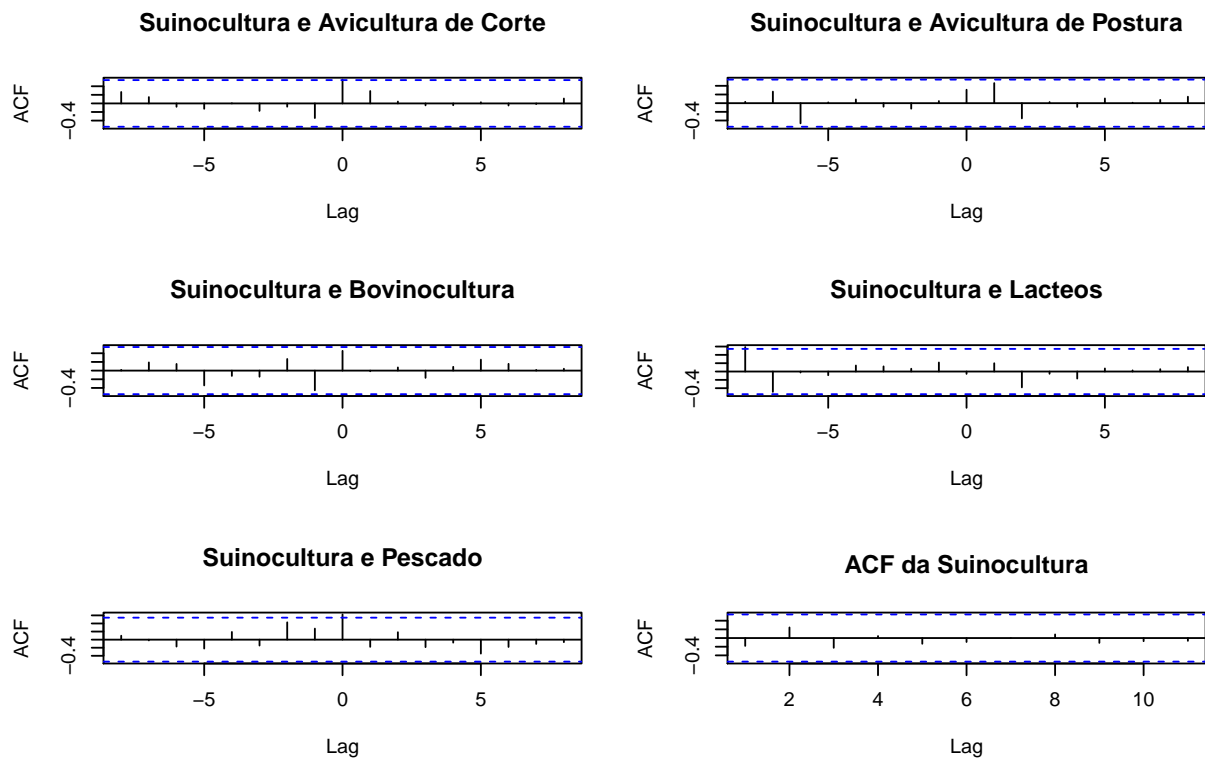
```
coef(cv.model, cv.model$lambda.min)
```

```
## 6 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 6.5890827
## AVC         .
## AVP         0.1112567
## BOV         .
## PESC        .
## SUIN        .
```

Regressão Lasso para Suinocultura

```
# Suinocultura
```

```
par(mfrow = c(3,2))
ccf(z_suino, z_avc, main="Suinocultura e Avicultura de Corte")
ccf(z_suino, z_avp, main="Suinocultura e Avicultura de Postura")
ccf(z_suino, z_bov, main="Suinocultura e Bovinocultura")
ccf(z_suino, z_lac, main="Suinocultura e Lacteos")
ccf(z_suino, z_pesc, main="Suinocultura e Pescado")
acf(z_suino, main = "ACF da Suinocultura")
```

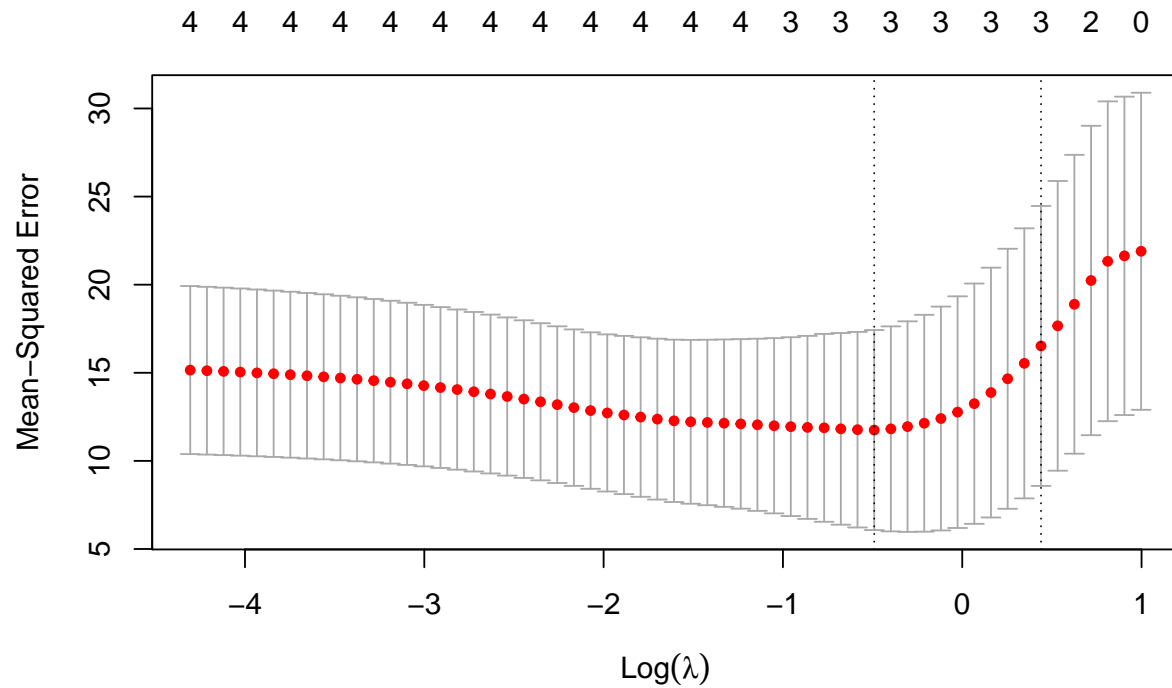


```
# Regressão Lasso para
x = model.matrix(SUIN~ .,data=data_anual)[,-1]
y = data_anual$SUIN
```

```
par(mfrow=c(1,1))
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
```

```
##
## Call: cv.glmnet(x = x, y = y, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min  0.612    17  11.75 5.676         3
## 1se  1.552     7  16.52 7.943         3
```

```
plot(cv.model)
```



```
coef(cv.model,cv.model$lambda.min)
```

```
## 6 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) -0.33554640
## AVC         0.21438530
## AVP         .
## BOV         0.08463707
## LAC         .
## PESC        0.55149018
```

```
# paramentros padrao para os plots
knitr::opts_chunk$set(fig.width = '\\textwidth',
                      fig.align = 'center',
                      out.width = "\\textwidth",
                      warning = FALSE, echo = TRUE)
```

```
library(robustbase)
library(knitr)
library(stargazer)
library(tidyverse)
library(gamlss)
library(car)
library(readxl)
library(MASS)
library(gridExtra)
```

```

library(ggplot2)
library(faraway)
require(BatchGetSymbols)
require(Amelia)
require(reshape2)
require(ggthemes)
require(plyr)
library(ggplot2)

suppressMessages(library(foreign))
suppressMessages(library(dynlm))
suppressMessages(library(car))
suppressMessages(library(lmtest))
suppressMessages(library(sandwich))
suppressMessages(library(fpp2))
suppressMessages(library(tseries))
suppressMessages(library(zoo))
suppressMessages(library(forecast))
library(BETS)
library(quantmod)
library(fpp2)
library(GeneCycle)
library(forecast)
library(randtests)
library(zoo)
library(TSA)
library(gridExtra)
library(FitAR)
library(glmnet)
library(lasso)
library(astsa)
library(lmtest)
library(forecast)
setwd("C:\\Users\\Rodrigo Araujo\\Documents\\IME-USP\\CEA 1\\dados")
setwd("C:\\Users\\Rodrigo Araujo\\Documents\\IME-USP\\CEA 1\\dados")
data = read_xlsx("IPCA_DADOS_AGRUPADOS.xlsx", sheet = 1)
data$Data <- as.Date(data$Data)
head(data)
zt2 <- ts(data[,2], frequency = 12, start = 2007, end = 2019)
zt3 <- ts(data[,3], frequency = 12, start = 2007, end = 2019)
zt4 <- ts(data[,4], frequency = 12, start = 2007, end = 2019)
zt5 <- ts(data[,5], frequency = 12, start = 2007, end = 2019)
zt6 <- ts(data[,6], frequency = 12, start = 2007, end = 2019)
zt7 <- ts(data[,7], frequency = 12, start = 2007, end = 2019)
zt8 <- ts(data[,8], frequency = 12, start = 2007, end = 2019)
zt9 <- ts(data[,9], frequency = 12, start = 2007, end = 2019)
zt10 <- ts(data[,10], frequency = 12, start = 2007, end = 2019)
zt11 <- ts(data[,11], frequency = 12, start = 2007, end = 2019)

zt12 <- ts(data[,12], frequency = 12, start = 2007, end = 2019)
zt13 <- ts(data[,13], frequency = 12, start = 2007, end = 2019)
zt14 <- ts(data[,14], frequency = 12, start = 2007, end = 2019)
zt15 <- ts(data[,15], frequency = 12, start = 2007, end = 2019)

```

```

zt16 <- ts(data[,16], frequency = 12, start = 2007, end = 2019)
zt17 <- ts(data[,17], frequency = 12, start = 2007, end = 2019)
zt18 <- ts(data[,18], frequency = 12, start = 2007, end = 2019)
zt19 <- ts(data[,19], frequency = 12, start = 2007, end = 2019)
zt20 <- ts(data[,20], frequency = 12, start = 2007, end = 2019)
zt21 <- ts(data[,21], frequency = 12, start = 2007, end = 2019)
zt22 <- ts(data[,22], frequency = 12, start = 2007, end = 2019)
zt23 <- ts(data[,23], frequency = 12, start = 2007, end = 2019)
zt24 <- ts(data[,24], frequency = 12, start = 2007, end = 2019)

plot(zt2,main="Série Temporal do Arroz", xlab= "Anos", ylab="IPCA")
#par(mfrow = c(2, 2))
plot(zt3,main="Série Temporal de Avicultura de Corte", xlab= "Anos", ylab="IPCA")
plot(zt4,main="Série Temporal de Avicultura de Postura", xlab= "Anos", ylab="IPCA")
plot(zt5,main="Série Temporal da Banana", xlab= "Anos", ylab="IPCA")
plot(zt6,main="Série Temporal da Batata", xlab= "Anos", ylab="IPCA")

#par(mfrow = c(3, 2))

plot(zt7,main="Série Temporal da Bovinocultura", xlab= "Anos", ylab="IPCA")
plot(zt8,main="Série Temporal do Cacau e Produtos", xlab= "Anos", ylab="IPCA")
plot(zt9,main="Série Temporal do Café", xlab= "Anos", ylab="IPCA")
plot(zt10,main="Série Temporal da Cebola", xlab= "Anos", ylab="IPCA")
plot(zt11,main="Série Temporal do Complexo Soja", xlab= "Anos", ylab="IPCA")
plot(zt12,main="Série Temporal do Complexo Sucroalc.", xlab= "Anos", ylab="IPCA")

#par(mfrow = c(3, 2))

plot(zt13,main="Série Temporal do Feijão", xlab= "Anos", ylab="IPCA")
plot(zt14,main="Série Temporal das Frutas", xlab= "Anos", ylab="IPCA")
plot(zt15,main="Série Temporal das Horticulturas", xlab= "Anos", ylab="IPCA")
plot(zt16,main="Série Temporal de Indefinido", xlab= "Anos", ylab="IPCA")
plot(zt17,main="Série Temporal do Laranja e Citrus", xlab= "Anos", ylab="IPCA")
plot(zt18,main="Série Temporal da Látceos", xlab= "Anos", ylab="IPCA")

#par(mfrow = c(3, 2))

plot(zt19,main="Série Temporal da Mandioca", xlab= "Anos", ylab="IPCA")
plot(zt20,main="Série Temporal do Milho", xlab= "Anos", ylab="IPCA")
plot(zt21,main="Série Temporal do Pescado", xlab= "Anos", ylab="IPCA")
plot(zt22,main="Série Temporal da Suínocultura", xlab= "Anos", ylab="IPCA")
plot(zt23,main="Série Temporal do Tomate", xlab= "Anos", ylab="IPCA")
plot(zt24,main="Série Temporal do Trigo", xlab= "Anos", ylab="IPCA")
par(mfrow = c(2, 1))
plot(zt21,main="Série Temporal do Pescado", xlab= "Anos", ylab="IPCA")
plot(zt18,main="Série Temporal do Látceos", xlab= "Anos", ylab="IPCA")
#900#650
par(mfrow = c(2, 1))
plot(zt7,main="Série Temporal da Bovinocultura", xlab= "Anos", ylab="IPCA")
plot(zt22,main="Série Temporal da Suínocultura", xlab= "Anos", ylab="IPCA")

```

```

par(mfrow = c(2, 1))
plot(zt3,main="Série Temporal de Avicultura de Corte", xlab= "Anos", ylab="IPCA")
plot(zt4,main="Série Temporal de Avicultura de Postura", xlab= "Anos", ylab="IPCA")

#Funções de Autocorrelações para Avicultura de Corte
par(mfrow = c(1, 2))
acf(zt3, main="ACF Avicultura de Corte")
pacf(zt3, main="PACF Avicultura de Corte")
#Funções de Autocorrelações para Avicultura de Postura
par(mfrow = c(1, 2))
acf(zt4, main="ACF Avicultura de Postura")
pacf(zt4, main="PACF Avicultura de Postura")
#Funções de Autocorrelações para Suinocultura
par(mfrow = c(1, 2))
acf(zt22, main="ACF Suínocultura")
pacf(zt22, main="PACF Suínocultura")
#Funções de Autocorrelações para Pescado
par(mfrow = c(1, 2))
acf(zt21, main="ACF Pescado", lag.max = 36)
pacf(zt21, main="PACF Pescado", lag.max = 36)
#Funções de Autocorrelações para Lácteos
par(mfrow = c(1, 2))
acf(zt18, main="ACF Lácteos", lag.max = 48)
pacf(zt18, main="PACF Lácteos", lag.max = 48)
#Funções de Autocorrelações para Bovinocultura
par(mfrow = c(1, 2))
acf(zt7, main="ACF Bovinocultura")
pacf(zt7, main="PACF Bovinocultura")
#Correlações cruzadas da Bovinocultura
par(mfrow = c(3,2))
ccf(zt7,zt3,main="Bovinocultura e Avicultura de Corte")
ccf(zt7,zt4,main="Bovinocultura e Avicultura de Postura")
ccf(zt7,zt18,main="Bovinocultura e Lácteos")
ccf(zt7,zt21,main="Bovinocultura e Pescados")
ccf(zt7,zt22,main="Bovinocultura e Suinocultura")
#Correlações cruzadas da Avicultura de Corte
par(mfrow = c(3,2))
ccf(zt3,zt4,main="Avicultura de Corte e Avicultura de Postura")
ccf(zt3,zt7,main="Avicultura de Corte e Bovinocultura")
ccf(zt3,zt18,main="Avicultura de Corte e Lácteos")
ccf(zt3,zt21,main="Avicultura de Corte e Pescados")
ccf(zt3,zt22,main="Avicultura de Corte e Suinocultura")

#Correlações cruzadas da Avicultura de Postura
par(mfrow = c(3,2))
ccf(zt4,zt3,main="Avicultura de Postura e Avicultura de Corte")
ccf(zt4,zt7,main="Avicultura de Postura e Bovinocultura")
ccf(zt4,zt18,main="Avicultura de Postura e Lácteos")
ccf(zt4,zt21,main="Avicultura de Postura e Pescados")
ccf(zt4,zt22,main="Avicultura de Postura e Suinocultura")
#Correlações cruzadas dos Lácteos
par(mfrow = c(3,2))

```

```

ccf(zt18,zt3,main="Lácteos e Avicultura de Corte")
ccf(zt18,zt4,main="Lácteos e Avicultura de Postura ")
ccf(zt18,zt7,main="Lácteos e Bovinocultura")
ccf(zt18,zt21,main="Lácteos e Pescados")
ccf(zt18,zt22,main="Lácteos e Suinocultura")
# Correlações cruzadas dos Pescados
par(mfrow = c(3,2))
ccf(zt21,zt3,main="Pescados e Avicultura de Corte")
ccf(zt21,zt4,main="Pescados e Avicultura de Postura")
ccf(zt21,zt7,main="Pescados e Bovinocultura")
ccf(zt21,zt18,main="Pescados e Lácteos")
ccf(zt21,zt22,main="Pescados e Suinocultura")

#Correlações cruzadas da Suinocultura
par(mfrow = c(3,2))
ccf(zt22,zt3,main="Suinocultura e Avicultura de Corte")
ccf(zt22,zt4,main="Suinocultura e Avicultura de Postura")
ccf(zt22,zt7,main="Suinocultura e Bovinocultura")
ccf(zt22,zt18,main="Suinocultura e Lacteos")
ccf(zt22,zt21,main="Suinocultura e Pescados")
#Essa função retorna a coluna com a lag a ser considerada na análise

funcao_lags = function(df,coluna,nome,lag){
  n = nrow(df)
  pre = rep(NA,lag)
  newcol = c(pre,coluna)
  for (k in 1:lag){
    df = rbind(df,rep(NA,ncol(df)))
  }
  df[nome] = newcol
  return (df)
}

#A função a baixo retira as variáveis do modelo em função do p-valor
tirar_variaveis = function(p,d,q,x,y){
  v = p + q + 1
  max = 0.06
  while (max > 0.05){
    model = Arima(y,order=c(p,d,q),xreg = x)
    ct = coeftest(model)
    pvalues = ct[(v+1):nrow(ct),4]
    maxi = which.max(pvalues)
    max = ct[v + maxi,4]
    if (max > 0.05) {
      x = x[,-maxi]
    }
  }
  lista = list(ct, x)
  return (lista)
}

#A seguir vamos selecionar apenas as variáveis de interesse para análise
data_cut = data[,c("Bovinocultura","Avicultura de Corte","Avicultura de Postura","Pescado","Lácteos","S
#Estruturando a base
df1<- funcao_lags(data_cut, data_cut$'Avicultura de Postura', 'avp9', 9)

```

```

df1 <- funcao_lags(df1, df1$Pescado, 'p3', 3)
df1 <- funcao_lags(df1, df1$Pescado, 'p10', 10)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'b1', 1)

df2 <- na.omit(df1)
#Separando variável preditora e as covariáveis
x = model.matrix(Bovinocultura~.,df2)[,-1]
y = df2$Bovinocultura
#Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

#Análise dos Resíduos
acf2(resid(fit))
#Análise dos resíduos e seleção de variáveis de acordo com p-valor
fit2 <- tirar_variaveis(0, 0, 0, x, y)
fit2[[1]]
xx <- fit2[2]
xx<- xx[[1]]

fit3 = Arima(y,order=c(0,0,0),xreg=xx)
fit3
coeftest(fit3)
acf2(fit3$residuals)

fit4 = Arima(y,order=c(1,0,0),xreg=xx)
fit4
coeftest(fit4)
checkresiduals(fit4)
acf2(fit4$residuals)

fit5 <- tirar_variaveis(1, 0, 0, xx, y)
fit5[[1]]
xx <- fit5[2]
xx<- xx[[1]]

fit6 = Arima(y,order=c(1,0,0),xreg=xx,fixed=c(NA,NA, NA, NA))
cof.fit6 = coeftest(fit6)
cof.fit6
checkresiduals(fit6)
acf2(fit6$residuals, main = "")

#Estruturando a base
df1<- funcao_lags(data_cut, data_cut$`Avicultura de Corte`, 'cort1', 1)

```



```

df1 <- funcao_lags(df1, df1$'Avicultura de Postura', 'pos12', 12)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov1', 1)
df1 <- funcao_lags(df1, df1$Pescado, 'pes4', 4)
df1 <- funcao_lags(df1, df1$Pescado, 'pes9', 9)
df1 <- funcao_lags(df1, df1$Suinocultura, 'sui1', 1)
df1 <- funcao_lags(df1, df1$Suinocultura, 'sui6', 6)

df2 <- na.omit(df1)
#Separando variável preditora e as covariáveis
x = model.matrix('Avicultura de Corte'~.,df2)[,-1]
y = df2$'Avicultura de Corte'
#Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

#Análise dos Resíduos
acf2(resid(fit))
#Seleção de variáveis
fit2 <- tirar_variaveis(0, 0, 0, x, y)
xx <- fit2[2]
xx <- xx[[1]]

fit3 = Arima(y,order=c(0,0,0), include.mean = FALSE, xreg=xx)
fit3
coeftest(fit3)
checkresiduals(fit3)
acf2(fit3$residuals, main = "")

# Estruturando a base
df1<- funcao_lags(data_cut, data_cut$Pescado, 'pes1', 1)
df1 <- funcao_lags(df1, df1$Pescado, 'pes5', 5)
df1 <- funcao_lags(df1, df1$Pescado, 'pes12', 12)

df1 <- funcao_lags(df1, df1$'Avicultura de Corte', 'cort3', 3)
df1 <- funcao_lags(df1, df1$'Avicultura de Corte', 'cort8', 8)

df1 <- funcao_lags(df1, df1$'Avicultura de Postura', 'pos2', 2)
df1 <- funcao_lags(df1, df1$'Avicultura de Postura', 'pos9', 9)

df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov1', 1)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov3', 3)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov7', 7)

df1 <- funcao_lags(df1, df1$Lácteos, 'lact2', 2)
df1 <- funcao_lags(df1, df1$Lácteos, 'lact8', 8)

df1 <- funcao_lags(df1, df1$Suinocultura, 'sui3', 3)

```

```

df2 <- na.omit(df1)
#Separando variável preditora e as covariáveis
x = model.matrix(Pescado~.,df2)[,-1]
y = df2$Pescado
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1
# Análise dos Resíduos
acf2(resid(fit))
# Análise dos resíduos e seleção de variáveis de acordo com p-valor
y = ts(y, frequency=12)

x = x[,-1]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-15]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-1]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-14]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-9]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-11]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-2]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-3]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

```

```

x = x[,-5]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-4]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

checkresiduals(fit3)
acf2(fit3$residuals, main = "")

x = x[,-2]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

x = x[,-2]
fit3 = Arima(y,order=c(0,0,0), seasonal = c(1, 0, 0),xreg=x)
coeftest(fit3)

checkresiduals(fit3)
acf2(fit3$residuals, main = "")
S

# Estruturando a base
df1<- funcao_lags(data_cut, data_cut$'Avicultura de Postura', 'avp1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Postura', 'avp12', 12)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc5', 5)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov3', 3)
df1 <- funcao_lags(df1, df1$Lácteos, 'lact11', 11)
df1 <- funcao_lags(df1, df1$Pescado, 'pes2', 2)
df1 <- funcao_lags(df1, df1$Pescado, 'pes9', 9)

df2 <- na.omit(df1)
#Separando variável preditora e as covariáveis
x = model.matrix('Avicultura de Postura'~.,df2)[,-1]
y = df2$'Avicultura de Postura'
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

# Análise dos Resíduos
acf2(resid(fit))
# Análise dos resíduos e seleção de variáveis de acordo com p-valor
fit2<- tirar_variaveis(0, 0, 0, x, y)
fit2[1]
xx <- fit2[2]
xx<- xx[[1]]

```

```

fit3 = Arima(y,order=c(0,0,0),xreg=xx)
coeftest(fit3)
checkresiduals(fit3)
acf2(fit3$residuals)

fit4 = Arima(y,order=c(3,0,0),xreg=xx,include.mean = FALSE,fixed=c(0,0,NA,NA,0,NA,NA,NA))
fit4
coeftest(fit4)
checkresiduals(fit4)
acf2(fit4$residuals, main = "")

# Estruturando a base

df1<- funcao_lags(data_cut, data_cut$Lácteos, 'lact1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Postura', 'avp1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc6', 6)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov2', 2)
df1 <- funcao_lags(df1, df1$Pescado, 'pes4', 4)
df1 <- funcao_lags(df1, df1$Pescado, 'pes9', 9)

df2 <- na.omit(df1)
#Separando variável preditora e as covariáveis
x = model.matrix(Lácteos~.,df2)[,-1]
y = df2$Lácteos
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

# Análise dos Resíduos
acf2(resid(fit))
# Análise dos resíduos e seleção de variáveis de acordo com p-valor
fit2 <- tirar_variaveis(0, 0, 0, x, y)

fit2[1]
xx <- fit2[2]
xx<- xx[[1]]

fit3 = Arima(y,order=c(0,0,0),xreg=xx,include.mean = FALSE)
coeftest(fit3)
checkresiduals(fit3)
acf2(fit3$residuals, main = "")

# Estruturando a base
df1<- funcao_lags(data_cut, data_cut$Suinocultura, 'su1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc1', 1)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc6', 6)
df1<- funcao_lags(df1, df1$'Avicultura de Corte', 'avc10', 10)
df1 <- funcao_lags(df1, df1$Bovinocultura, 'bov1', 1)
df2 <- na.omit(df1)

```

```

# Separando variável preditora e as covariáveis
x = model.matrix(Suinocultura~.,df2)[,-1]
y = df2$Suinocultura
# Criando o modelo de Regressão Simples
fit1 <- summary(fit <- lm(y~x))
fit1

# Análise dos Resíduos
acf2(resid(fit))
# Análise dos resíduos e seleção de variáveis de acordo com p-valor

fit2 <- tirar_variaveis(0, 0, 0, x, y)

fit2[1]
xx <- fit2[2]
xx<- xx[[1]]

fit3 = Arima(y,order=c(0,0,0),xreg=xx)
coeftest(fit3)
checkresiduals(fit3)
acf2(fit3$residuals)

fit4 = Arima(y,order=c(2,0,0),xreg=xx,fixed =c(0,NA,NA,NA,NA,NA))
fit4
coeftest(fit4)
checkresiduals(fit4)
acf2(fit4$residuals, main = "")

library(readxl)
data_anual = read_xlsx("C:\\Users\\Rodrigo Araujo\\Documents\\IME-USP\\CEA 1\\dados\\Cadeia-Ano.xlsx")
# Análise das séries temporais anuais
head(data_anual)
# Análise Descritiva
z_avc = data_anual$`Avicultura de Corte`
z_avc = ts(z_avc)

z_avp = data_anual$`Avicultura Postura`
z_avp = ts(z_avp)

z_bov = data_anual$`Bovinocultura de corte`
z_bov = ts(z_bov)

z_lac = data_anual$`Lácteos`
z_lac = ts(z_lac)

z_pesc = data_anual$Pescado
z_pesc = ts(z_pesc)

z_suino = data_anual$Suinocultura
z_suino = ts(z_suino)
# Análise Descritiva

```

```

par(mfrow = c(3,2))
plot(z_avc,main="Série Temporal da Avicultura de Corte", xlab= "Anos", ylab="IPCA")
plot(z_avp,main="Série Temporal da Avicultura de Postura", xlab= "Anos", ylab="IPCA")
plot(z_lac,main="Série Temporal do Látceos", xlab= "Anos", ylab="IPCA")
plot(z_pesc,main="Série Temporal do Pescado", xlab= "Anos", ylab="IPCA")
plot(z_bov,main="Série Temporal da Bovinocultura", xlab= "Anos", ylab="IPCA")
plot(z_suino,main="Série Temporal da Suinocultura", xlab= "Anos", ylab="IPCA")
# Variáveis do modelo
library(glmnet)

colnames(data_anual) = c("ANO", "AVC", "AVP", "BOV", "LAC", "PESC", "SUIN")
data_anual = data_anual[,-1]

#Correlações cruzadas da Bovinocultura
par(mfrow = c(3,2))
ccf(z_bov,z_avc,main="Bovinocultura e Avicultura de Corte")
ccf(z_bov,z_avp,main="Bovinocultura e Avicultura de Postura")
ccf(z_bov,z_lac,main="Bovinocultura e Látceos")
ccf(z_bov,z_pesc,main="Bovinocultura e Pescado")
ccf(z_bov,z_suino,main="Bovinocultura e Suinocultura")
acf(z_bov, main = "ACF da Bovinocultura")

# Regressão LASSO
x = model.matrix(BOV~ .,data=data_anual)[,-1]
y = data_anual$BOV

cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
par(mfrow=c(1,1))
plot(cv.model)

coef(cv.model,cv.model$lambda.min)

# Pescados
par(mfrow = c(3,2))
ccf(z_pesc,z_avc,main="Pescado e Avicultura de Corte")
ccf(z_pesc,z_avp,main="Pescado e Avicultura de Postura")
ccf(z_pesc,z_bov,main="Pescado e Bovinocultura")
ccf(z_pesc,z_lac,main="Pescado e Látceos")
ccf(z_pesc,z_suino,main="Pescado e Suinocultura")
acf(z_pesc, main = "ACF do Pescado")

# Regressão Lasso
x = model.matrix(PESC~ .,data=data_anual)[,-1]
y = data_anual$PESC

cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
par(mfrow=c(1,1))
plot(cv.model)

```

```

coef(cv.model,cv.model$lambda.min)

# Avicultura de Corte

par(mfrow = c(3,2))
ccf(z_avc,z_avp,main="Avicultura de Corte e Avicultura de Postura")
ccf(z_avc,z_bov,main="Avicultura de Corte e Bovinocultura")
ccf(z_avc,z_lac,main="Avicultura de Corte e Lácteos")
ccf(z_avc,z_pesc,main="Avicultura de Corte e Pescado")
ccf(z_avc,z_suino,main="Avicultura de Corte e Suinocultura")
acf(z_avc, main = "ACF da Avicultura de Corte")

## Regressão Lasso

x = model.matrix(AVC~ .,data=data_anual)[,-1]
y = data_anual$AVC

cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
par(mfrow=c(1,1))
plot(cv.model)

coef(cv.model,cv.model$lambda.min)
# Avicultura de Postura

par(mfrow = c(3,2))
ccf(z_avp,z_avc,main="Avicultura de Postura e Avicultura de Corte")
ccf(z_avp,z_bov,main="Avicultura de Postura e Bovinocultura")
ccf(z_avp,z_lac,main="Avicultura de Postura e Lácteos")
ccf(z_avp,z_pesc,main="Avicultura de Postura e Pescado")
ccf(z_avp,z_suino,main="Avicultura de Postura e Suinocultura")
acf(z_avp, main = "ACF Avicultura de Postura")

# Regressão Lasso

x = model.matrix(AVP~ .,data=data_anual)[,-1]
y = data_anual$AVP

par(mfrow=c(1,1))
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
plot(cv.model)

coef(cv.model,cv.model$lambda.min)

# Lacteos

par(mfrow = c(3,2))
ccf(z_lac,z_avc,main="Lácteos e Avicultura de Corte")
ccf(z_lac,z_avp,main="Lácteos e Avicultura de Postura")
ccf(z_lac,z_bov,main="Lácteos e Bovinocultura")
ccf(z_lac,z_pesc,main="Lácteos e Pescado")
ccf(z_lac,z_suino,main="Lácteos e Suinocultura")
acf(z_lac, main = "ACF do Lácteos")

```

```

# Regressão Lasso
x = model.matrix(LAC~ .,data=data_anual)[,-1]
y = data_anual$LAC

par(mfrow=c(1,1))
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
plot(cv.model)

coef(cv.model,cv.model$lambda.min)

# Suinocultura

par(mfrow = c(3,2))
ccf(z_suino,z_avc,main="Suinocultura e Avicultura de Corte")
ccf(z_suino,z_avp,main="Suinocultura e Avicultura de Postura")
ccf(z_suino,z_bov,main="Suinocultura e Bovinocultura")
ccf(z_suino,z_lac,main="Suinocultura e Lacteos")
ccf(z_suino,z_pesc,main="Suinocultura e Pescado")
acf(z_suino, main = "ACF da Suinocultura")

# Regressão Lasso para
x = model.matrix(SUIN~ .,data=data_anual)[,-1]
y = data_anual$SUIN

par(mfrow=c(1,1))
cv.model = cv.glmnet(x,y,alpha = 1)
cv.model
plot(cv.model)

coef(cv.model,cv.model$lambda.min)

```