## Time Series Analysis Homework07 Explaination

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December 08, 2024

- 5. Consider the well-known time series data "co2" (monthly carbon dioxide readings through 11 years in Alert, Canada).
- 5.a. Fit a deterministic regression model in terms of months and time. Are the regression coefficients significant? What is the adjusted R-squared? (Note that the month variable should be treated as categorical and transformed into 11 dummy variables.)

```
library(forecast)
library(TSA)
library(tseries)
library(tidyverse)

data <- read.csv("C:/Git_Code/Some-practice/TSA HW07.co2.csv")
data$month <- factor(data$month, levels = unique(data$month))
model <- lm(co2_level ~ time_trend + month, data = data)
summary(model)</pre>
```

```
##
## Call:
## lm(formula = co2_level ~ time_trend + month, data = data)
##
## Residuals:
##
       Min
                  1Q
                       Median
                                    30
                                            Max
## -1.73874 -0.59689 -0.06947 0.54086
##
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3290.5412
                             44.1790 -74.482 < 2e-16 ***
## time_trend
                              0.0221 82.899 < 2e-16 ***
                   1.8321
## monthFeb
                   0.6682
                              0.3424
                                       1.952 0.053319 .
## monthMar
                   0.9637
                              0.3424
                                       2.815 0.005715 **
                              0.3424
                   1.2311
                                       3.595 0.000473 ***
## monthApr
## monthMay
                   1.5275
                              0.3424
                                       4.460 1.87e-05 ***
## monthJun
                  -0.6761
                              0.3425
                                      -1.974 0.050696 .
## monthJul
                  -7.2851
                              0.3426 -21.267
                                             < 2e-16 ***
                              0.3426 -39.232 < 2e-16 ***
## monthAug
                 -13.4414
## monthSep
                 -12.8205
                              0.3427 -37.411
                                              < 2e-16 ***
## monthOct
                  -8.2604
                              0.3428 -24.099 < 2e-16 ***
## monthNov
                  -3.9277
                              0.3429 -11.455 < 2e-16 ***
## monthDec
                  -1.3367
                              0.3430 -3.897 0.000161 ***
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8029 on 119 degrees of freedom
## Multiple R-squared: 0.9902, Adjusted R-squared: 0.9892
## F-statistic: 997.7 on 12 and 119 DF, p-value: < 2.2e-16

cat("Adjusted R-squared:", summary(model)$adj.r.squared)</pre>
```

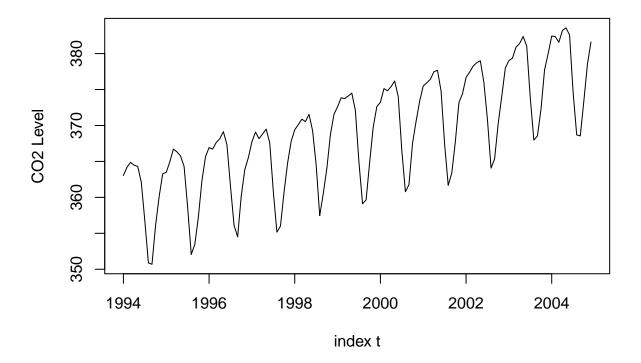
## Adjusted R-squared: 0.9891657

**Explanation:** All regression coefficients are significant except monthFeb and monthJun. The adjusted R-squared is 0.9891657.

5.b. Identify, estimate the SARIMA model for the co2 level.

```
co2_ts <- ts(data$co2_level, start = c(1994, 1), frequency = 12)
plot(co2_ts, main = "CO2 Levels Over Time", ylab = "CO2 Level", xlab = "index t")</pre>
```

## **CO2 Levels Over Time**

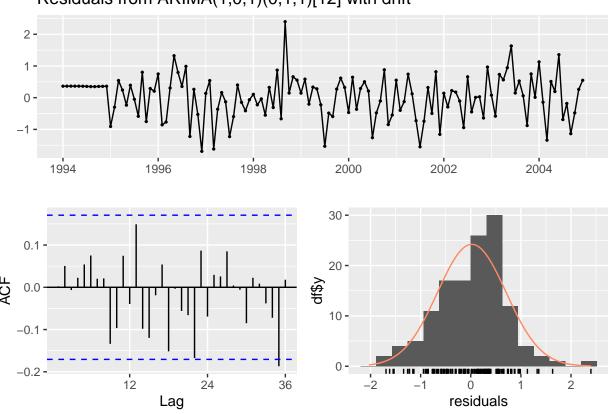


sarima\_model <- auto.arima(co2\_ts, seasonal = TRUE, stepwise = FALSE, approximation = FALSE)
summary(sarima\_model)</pre>

```
## Series: co2_ts
## ARIMA(1,0,1)(0,1,1)[12] with drift
##
##
  Coefficients:
##
            ar1
                     ma1
                              sma1
                                     drift
##
         0.8349
                -0.4630
                          -0.8487
                                    0.1520
##
        0.0819
                  0.1246
                           0.1274
                                    0.0052
##
## sigma^2 = 0.5288: log likelihood = -136.09
  AIC=282.18
               AICc=282.7
                             BIC=296.11
##
##
   Training set error measures:
                                RMSE
                                           MAE
                                                       MPE
                                                                MAPE
                                                                          MASE
##
                        ME
  Training set 0.02075345 0.6817172 0.542085 0.005102291 0.1469965 0.288126
##
##
                       ACF1
## Training set 0.002372469
```

checkresiduals(sarima\_model)

## Residuals from ARIMA(1,0,1)(0,1,1)[12] with drift



```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(1,0,1)(0,1,1)[12] with drift
## Q* = 25.4, df = 21, p-value = 0.2302
##
## Model df: 3. Total lags used: 24
```

**Explanation:** We can see that SARIMA(1,0,1)(0,1,1)[12] can fit the data and Ljung Box test also shows that the residual is stationary process.

5.c. Compare the two models above, what do you observe?

```
calculate_mape <- function(actual, predicted) {
   return(mean(abs((actual - predicted) / actual)) * 100)
}

deterministic_predictions <- as.numeric(predict(model, newdata = data))
sarima_predictions <- as.numeric(fitted(sarima_model))

mape_deterministic <- calculate_mape(data$co2_level, deterministic_predictions)
mape_sarima <- calculate_mape(data$co2_level, sarima_predictions)

cat("MAPE for Deterministic Regression:", mape_deterministic, "%\n")

## MAPE for Deterministic Regression: 0.1693098 %

cat("MAPE for SARIMA Model:", mape_sarima, "%\n")</pre>
```

## MAPE for SARIMA Model: 0.1469965 %

**Explanation:** We can see that the MAPE for Deterministic Regression is 0.1693098 % and MAPE for SARIMA Model is 0.1469965 %. Thus, we can conclude that SARIMA is slightly better than Deterministic Regression. Both models has a great performance in the dataset.