FLT Forecasting

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```
library(tidyverse)
## Warning: package 'ggplot2' was built under R version 4.3.3
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr 1.1.2
                      v readr
                                 2.1.4
                    v stringr 1.5.0
## v forcats 1.0.0
## v ggplot2 3.5.0
                   v tibble 3.2.1
## v lubridate 1.9.2
                      v tidyr
                                1.3.0
## v purrr
             1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
rescaled = read_csv("data_rescaled.csv")
## New names:
## Rows: 249 Columns: 18
## -- Column specification
## ------ Delimiter: "," dbl
## (18): ...1, Year, Month, Dom_Pax (in millions), Int_Pax (in millions), P...
## i Use 'spec()' to retrieve the full column specification for this data. i
## Specify the column types or set 'show_col_types = FALSE' to quiet this message.
## * '' -> '...1'
rescaled
## # A tibble: 249 x 18
##
      ...1 Year Month 'Dom_Pax (in millions)' 'Int_Pax (in millions)'
##
     <dbl> <dbl> <dbl>
                                       <dbl>
                                                             <dbl>
## 1
        1 2003
                                       43.0
                                                              4.91
## 2
         2 2003
                                       41.2
                                                              4.25
## 3
       3 2003
                    3
                                       50.0
                                                              5.01
## 4
       4 2003
                                       47.0
                                                             4.35
## 5
       5 2003
                                       49.2
                                                              4.61
                   5
        6 2003
## 6
                                       52.2
                                                              5.41
## 7
        7 2003
                   7
                                       55.8
                                                             6.19
```

53.9

44.2

6.27

4.82

8

9

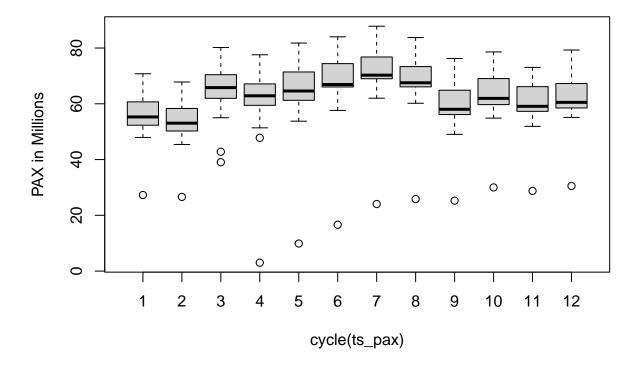
8 2003

9 2003

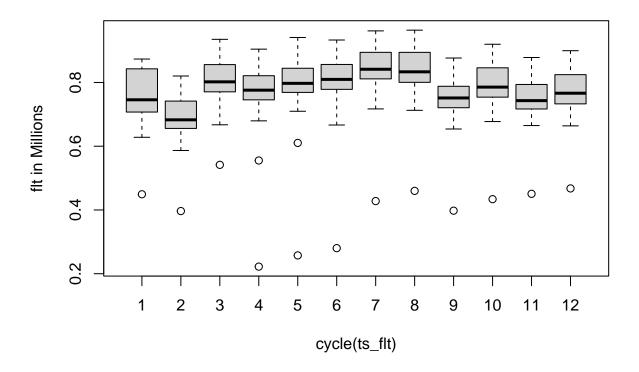
9

```
## 10
         10 2003
                                           49.9
                                                                    4.92
                     10
## # i 239 more rows
## # i 13 more variables: 'Pax (in millions)' <dbl>,
       'Dom_Flt (in millions)' <dbl>, 'Int_Flt (in millions)' <dbl>,
       'Flt (in millions)' <dbl>, 'Dom_RPM (in millions)' <dbl>,
       'Int_RPM (in millions)' <dbl>, 'RPM (in millions)' <dbl>,
## #
       'Dom ASM (in millions)' <dbl>, 'Int ASM (in millions)' <dbl>,
       'ASM (in millions)' <dbl>, Dom_LF <dbl>, Int_LF <dbl>, LF <dbl>
## #
ts_pax = ts(rescaled_p^r)ax (in millions), start = c(2003, 1), end = c(2023, 9),
            frequency = 12)
boxplot(ts_pax~cycle(ts_pax), main="Check Seasonality of PAX", ylab="PAX in Millions")
```

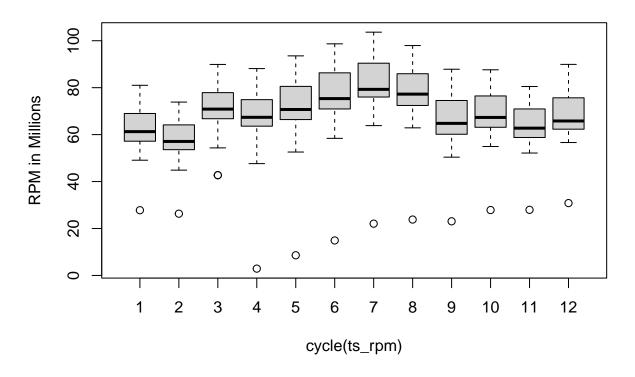
Check Seasonality of PAX



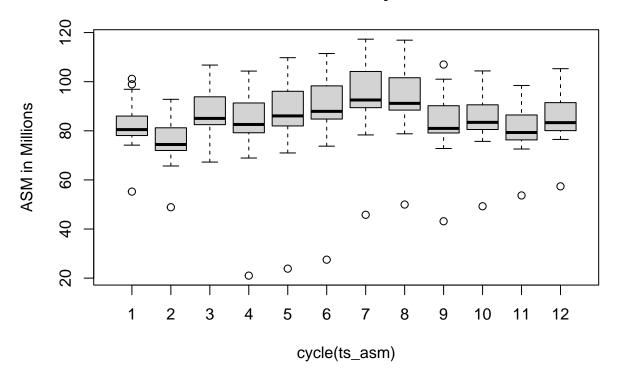
Check Seasonality of FLT



Check Seasonality of RPM

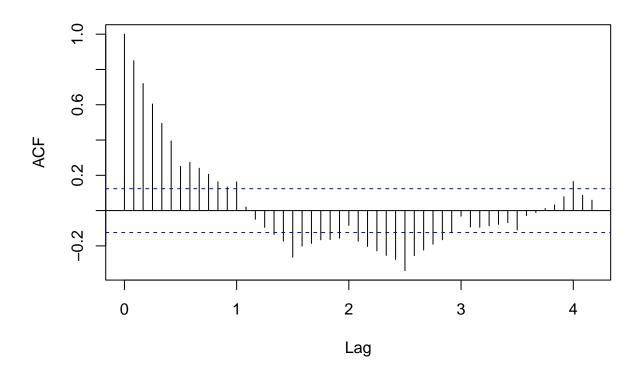


Check Seasonality of ASM



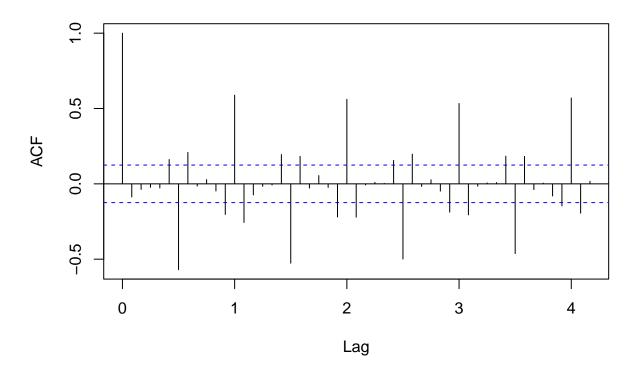
acf(ts_pax, lag.max=50)

Series ts_pax



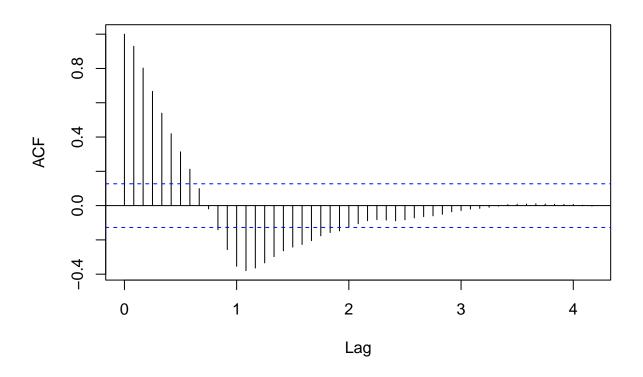
acf(diff(ts_pax, lag=1), lag.max=50)

Series diff(ts_pax, lag = 1)



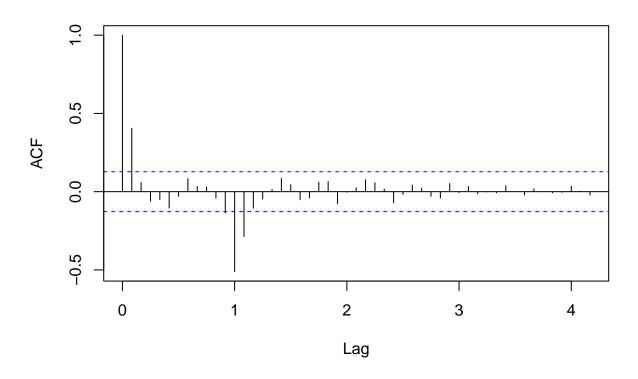
acf(diff(ts_pax, lag=12), lag.max=50, main="Cyclical trend not completely removed")

Cyclical trend not completely removed



Do seasonal differencing of the regular differencing
acf(diff(diff(ts_pax, lag=1), lag=12), lag.max=50, main="Seasonal diff of Regular diff.
 Leaves ACF of stationary random term")

Seasonal diff of Regular diff. Leaves ACF of stationary random term



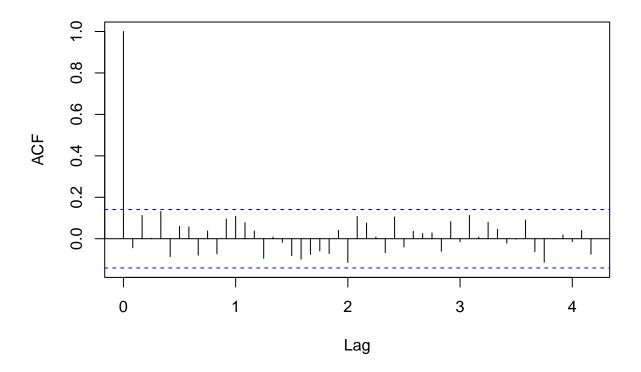
Forecast PAX (# of Passengers)

The idea is to use pre-covid data to train model and forecast

```
ts_pax = ts(rescaled_p^r)ax (in millions), start = c(2003, 1), end = c(2023, 9),
            frequency = 12)
# use data before 2019/1 as training
training=window(ts_pax, end=c(2019,1), frequency=12)
# use data from 2019/2 to 2020/2 as test
test=window(ts_pax, start=c(2019,2), end=c(2020,2), frequency=12)
test
##
             Jan
                      Feb
                               Mar
                                         Apr
                                                  May
                                                           Jun
                                                                     Jul
                                                                              Aug
## 2019
                 63.55123 80.18159 76.39926 81.31647 83.80858 86.92585 83.75119
## 2020 70.76777 67.81321
             Sep
                      Oct
                               Nov
## 2019 72.56932 78.60060 73.05753 79.28466
## 2020
model1=arima(training,order=c(0,1,1), seas=list(order=c(0,1,1), 12))
model1
##
## Call:
## arima(x = training, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1),
##
       12))
```

```
##
## Coefficients:
##
                     sma1
##
         -0.4600 -0.6600
         0.0599
                   0.0801
## s.e.
##
## sigma^2 estimated as 1.37: log likelihood = -287.27, aic = 580.55
RMSE.of.fit = sqrt(model1$sigma2)
RMSE.of.fit
## [1] 1.17034
range(rescaled$`Pax (in millions)`)
## [1] 3.013899 87.810772
acf(residuals(model1), lag.max=50)
```

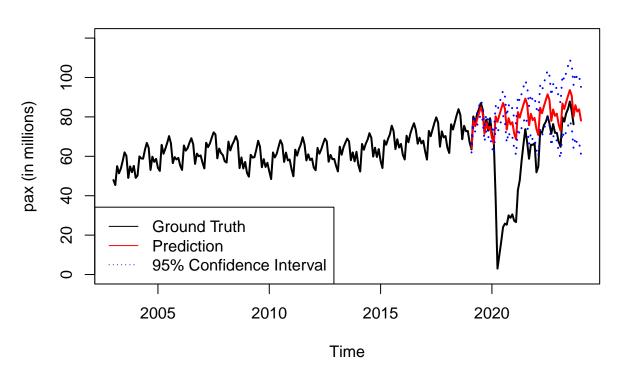
Series residuals(model1)



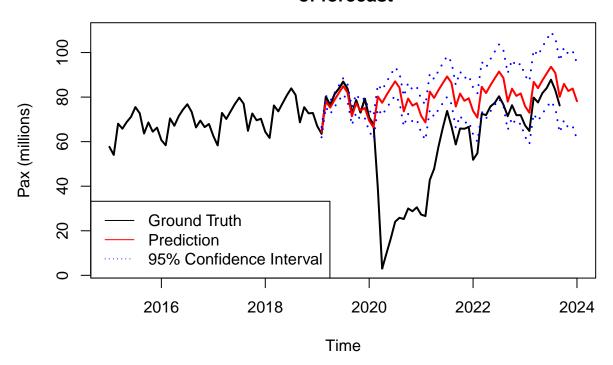
```
forecast=predict(model1,n.ahead=60,se.fit=TRUE)

pcil=ts((forecast$pred-1.96*forecast$se),start=c(2019,2),freq=12)
pciu=ts((forecast$pred+1.96*forecast$se),start=c(2019,2),freq=12)
```

plot



Closeup view of forecast



summary(ts_pax)

Min. 1st Qu. Median Mean 3rd Qu. Max. ## 3.014 57.665 63.899 62.602 69.447 87.811