time series

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R-Time series Analysis

Any metric is measured over a regular time forms a time series.

Time series-Is a collection of observations made sequentially in time. Creating a Time series-ts() function is used to create a time series

E.g timeseries<-ts(data,start,end,frequency)

Data-Vector or matrix which contains values used in time series **Start**-start time for the first observation. **End**-end time for the last observation. **Frequency**-specifies number of observations per unit time Example ,Consider the annual snowfall details at a place starting from January 2013.

```
snowfall <-
c(790,1170.8,860.1,1330.6,630.4,911.5,683.5,996.6,783.2,982,881.8,1021)
timeseries <- ts(snowfall,start = c(2013,1),frequency = 12)
timeseries
```

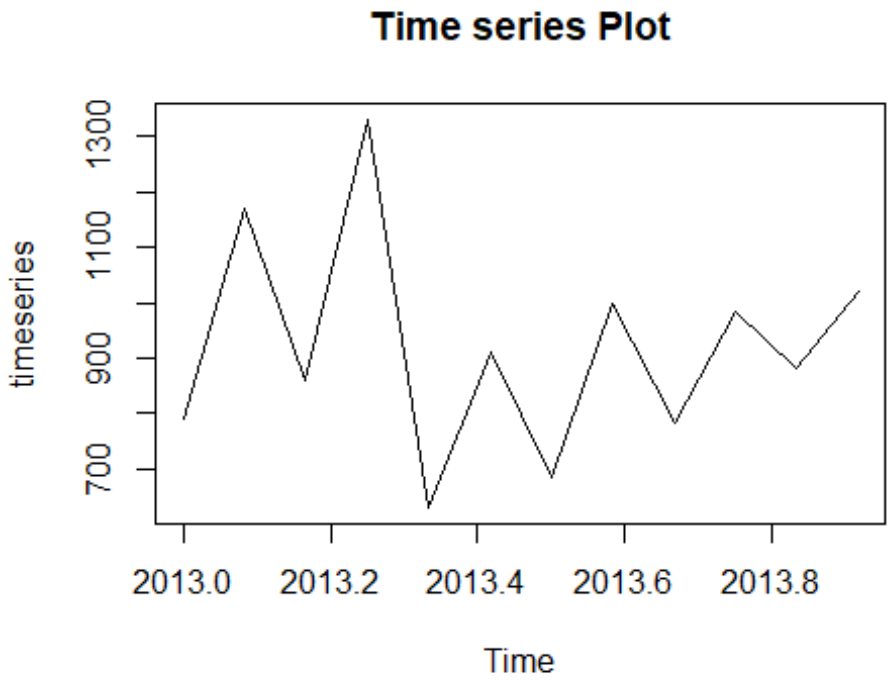
```
##         Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct
## 2013  790.0 1170.8  860.1 1330.6  630.4  911.5  683.5  996.6  783.2  982.0
##         Nov    Dec
## 2013  881.8 1021.0
```

```
library(tseries)
```

```
## Warning: package 'tseries' was built under R version 4.1.3
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
plot.ts(timeseries,main="Time series Plot")
```



##

Stationary Time Series

A series is stationary if ;

1. Mean value of series is constant over time.That implies that trend component is declared null.

2.Variance should not increase over time.

3.The seasonality effect should be minimal.

i.e it is a trendseasonal pattern .which resembles a random white noise regardless of time interval observed.

NOTE:Stationary Time Series is the one whose statistical properties like mean ,variance ,and autocorrrelation, etc are all constant over time.
##

Differencing time series data to make it stationary

**forex data AUD* clearing allvariables in the Workspace

```
rm(list = ls())
#loading the forecasting package
library(fpp2)

## Warning: package 'fpp2' was built under R version 4.1.3
```

```
## -- Attaching packages --------------------------------------- fpp2
2.4 --

## v ggplot2   3.3.5     v fma       2.4
## v forecast  8.16      v expsmooth 2.3

## Warning: package 'forecast' was built under R version 4.1.3

## Warning: package 'fma' was built under R version 4.1.3

## Warning: package 'expsmooth' was built under R version 4.1.3

##
```

Importing the data

```
jpy=read.csv("C:\\Users\\dennis\\Downloads\\AUD_JPY (1 T).csv")
jpy
```

```
##           Date     Time AUD.JPY
## 1   2022-06-29 06:55:12  93.556
## 2   2022-06-29 06:55:13  93.566
## 3   2022-06-29 06:55:14  93.566
## 4   2022-06-29 06:55:15  93.565
## 5   2022-06-29 06:55:16  93.561
## 6   2022-06-29 06:55:17  93.561
## 7   2022-06-29 06:55:18  93.560
## 8   2022-06-29 06:55:19  93.559
## 9   2022-06-29 06:55:20  93.557
## 10  2022-06-29 06:55:21  93.548
## 11  2022-06-29 06:55:22  93.560
## 12  2022-06-29 06:55:23  93.560
## 13  2022-06-29 06:55:24  93.562
## 14  2022-06-29 06:55:25  93.562
## 15  2022-06-29 06:55:26  93.564
## 16  2022-06-29 06:55:27  93.559
## 17  2022-06-29 06:55:28  93.561
## 18  2022-06-29 06:55:29  93.560
## 19  2022-06-29 06:55:30  93.560
## 20  2022-06-29 06:55:31  93.552
## 21  2022-06-29 06:55:32  93.550
## 22  2022-06-29 06:55:33  93.555
## 23  2022-06-29 06:55:34  93.550
## 24  2022-06-29 06:55:35  93.548
## 25  2022-06-29 06:55:36  93.544
## 26  2022-06-29 06:55:37  93.543
## 27  2022-06-29 06:55:38  93.541
## 28  2022-06-29 06:55:39  93.542
## 29  2022-06-29 06:55:40  93.546
## 30  2022-06-29 06:55:41  93.547
## 31  2022-06-29 06:55:42  93.552
## 32  2022-06-29 06:55:43  93.552
```

```
## 33  2022-06-29 06:55:44  93.554
## 34  2022-06-29 06:55:45  93.555
## 35  2022-06-29 06:55:46  93.551
## 36  2022-06-29 06:55:47  93.554
## 37  2022-06-29 06:55:48  93.556
## 38  2022-06-29 06:55:49  93.559
## 39  2022-06-29 06:55:50  93.564
## 40  2022-06-29 06:55:51  93.565
## 41  2022-06-29 06:55:52  93.565
## 42  2022-06-29 06:55:53  93.565
## 43  2022-06-29 06:55:54  93.566
## 44  2022-06-29 06:55:55  93.567
## 45  2022-06-29 06:55:56  93.561
## 46  2022-06-29 06:55:57  93.564
## 47  2022-06-29 06:55:58  93.566
## 48  2022-06-29 06:55:59  93.569
## 49  2022-06-29 06:56:00  93.570
## 50  2022-06-29 06:56:01  93.573
## 51  2022-06-29 06:56:02  93.571
## 52  2022-06-29 06:56:03  93.567
## 53  2022-06-29 06:56:04  93.563
## 54  2022-06-29 06:56:05  93.567
## 55  2022-06-29 06:56:06  93.568
## 56  2022-06-29 06:56:07  93.566
## 57  2022-06-29 06:56:08  93.565
## 58  2022-06-29 06:56:09  93.567
## 59  2022-06-29 06:56:10  93.572
## 60  2022-06-29 06:56:11  93.567
## 61  2022-06-29 06:56:12  93.559
## 62  2022-06-29 06:56:13  93.559
## 63  2022-06-29 06:56:14  93.559
## 64  2022-06-29 06:56:15  93.549
## 65  2022-06-29 06:56:16  93.545
## 66  2022-06-29 06:56:17  93.540
## 67  2022-06-29 06:56:18  93.545
## 68  2022-06-29 06:56:19  93.545
## 69  2022-06-29 06:56:20  93.547
## 70  2022-06-29 06:56:21  93.549
## 71  2022-06-29 06:56:22  93.544
## 72  2022-06-29 06:56:23  93.544
## 73  2022-06-29 06:56:24  93.544
## 74  2022-06-29 06:56:25  93.543
## 75  2022-06-29 06:56:26  93.543
## 76  2022-06-29 06:56:27  93.545
## 77  2022-06-29 06:56:28  93.542
## 78  2022-06-29 06:56:29  93.543
## 79  2022-06-29 06:56:30  93.541
## 80  2022-06-29 06:56:31  93.546
## 81  2022-06-29 06:56:32  93.547
## 82  2022-06-29 06:56:33  93.543
```

```
## 83  2022-06-29 06:56:34  93.543
## 84  2022-06-29 06:56:35  93.539
## 85  2022-06-29 06:56:36  93.535
## 86  2022-06-29 06:56:37  93.540
## 87  2022-06-29 06:56:38  93.541
## 88  2022-06-29 06:56:39  93.540
## 89  2022-06-29 06:56:40  93.536
## 90  2022-06-29 06:56:41  93.537
## 91  2022-06-29 06:56:42  93.541
## 92  2022-06-29 06:56:43  93.537
## 93  2022-06-29 06:56:44  93.540
## 94  2022-06-29 06:56:45  93.541
## 95  2022-06-29 06:56:46  93.543
## 96  2022-06-29 06:56:47  93.538
## 97  2022-06-29 06:56:48  93.542
## 98  2022-06-29 06:56:49  93.544
## 99  2022-06-29 06:56:50  93.542
## 100 2022-06-29 06:56:51  93.543
```

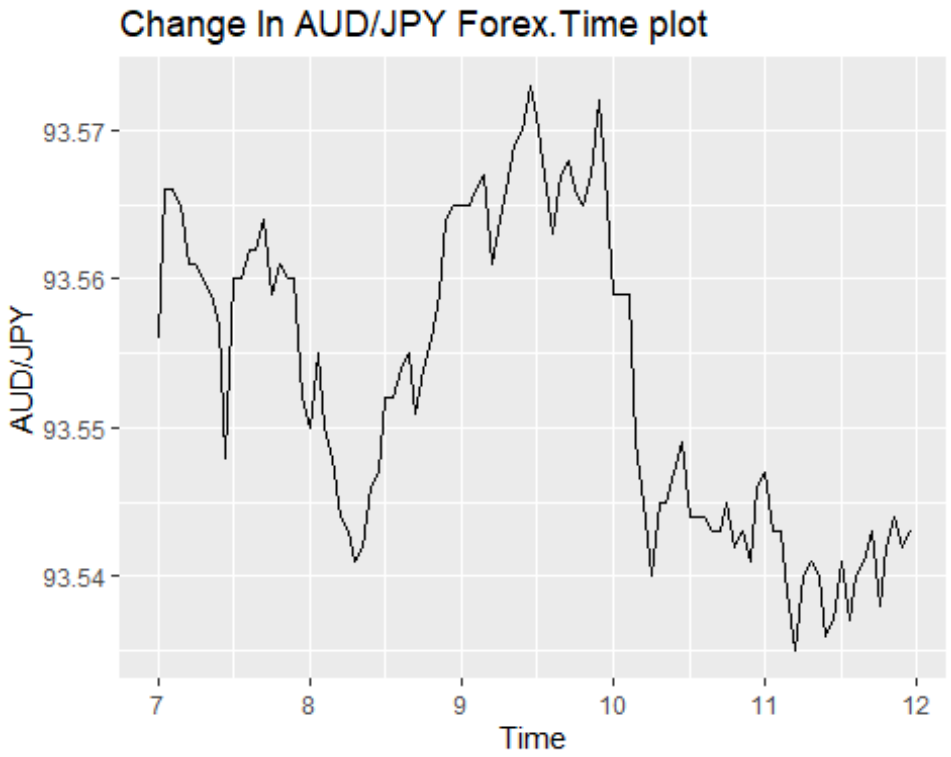
```
jpy=jpy[,3]
jpy
```

```
##   [1] 93.556 93.566 93.566 93.565 93.561 93.561 93.560 93.559 93.557
93.548
##  [11] 93.560 93.560 93.562 93.562 93.564 93.559 93.561 93.560 93.560
93.552
##  [21] 93.550 93.555 93.550 93.548 93.544 93.543 93.541 93.542 93.546
93.547
##  [31] 93.552 93.552 93.554 93.555 93.551 93.554 93.556 93.559 93.564
93.565
##  [41] 93.565 93.565 93.566 93.567 93.561 93.564 93.566 93.569 93.570
93.573
##  [51] 93.571 93.567 93.563 93.567 93.568 93.566 93.565 93.567 93.572
93.567
##  [61] 93.559 93.559 93.559 93.549 93.545 93.540 93.545 93.545 93.547
93.549
##  [71] 93.544 93.544 93.544 93.543 93.543 93.545 93.542 93.543 93.541
93.546
##  [81] 93.547 93.543 93.543 93.539 93.535 93.540 93.541 93.540 93.536
93.537
##  [91] 93.541 93.537 93.540 93.541 93.543 93.538 93.542 93.544 93.542
93.543
```

```
#converting to time series data. Time is in seconds i.e, changes occuring in
every second
jpyt=ts(jpy,start = c(7,1),frequency = 20)
```

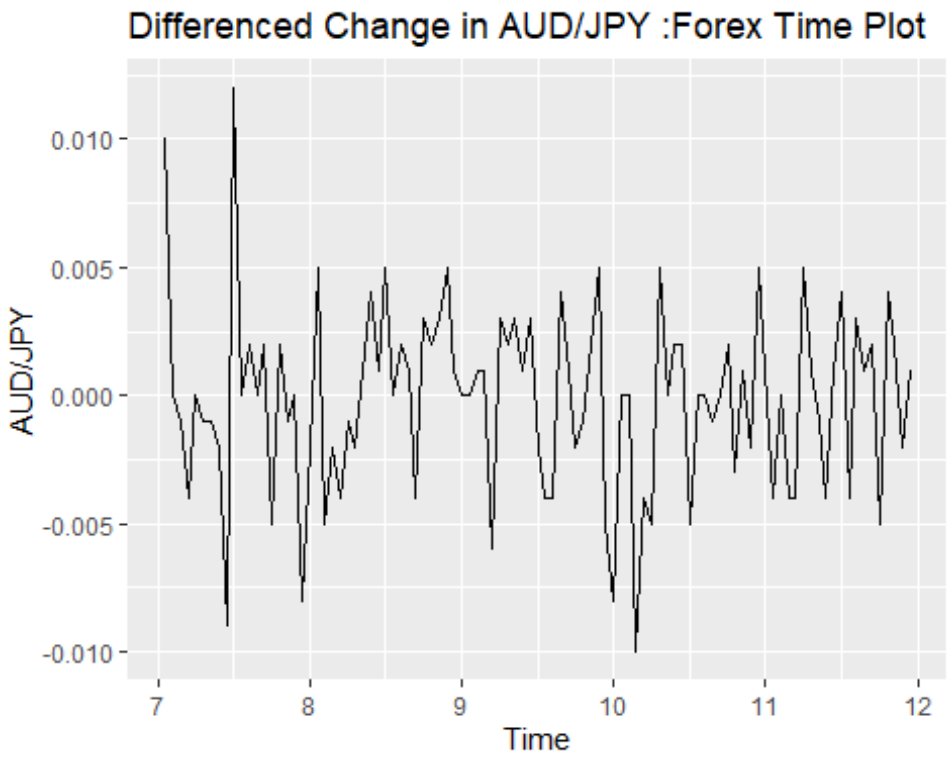
Preliminary analysis

```
#Time plot
autoplot(jpyt)+ggtitle("Change In AUD/JPY Forex.Time plot")+
  ylab("AUD/JPY")
```



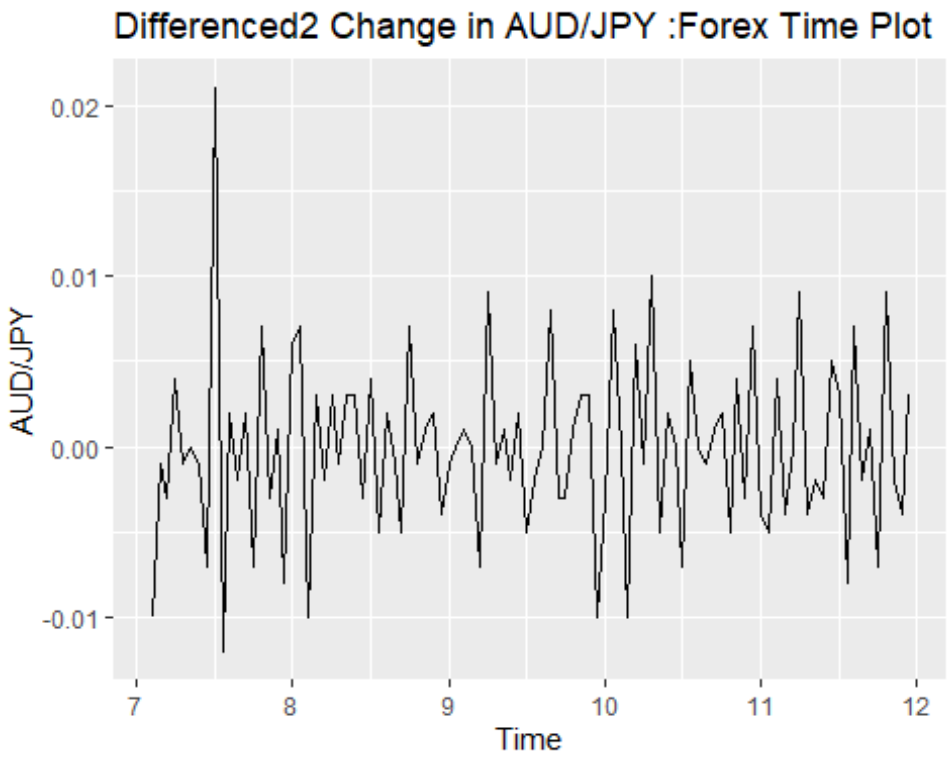
Differencing the data to remove trend

```
dy=diff(jpyt)
#plotting differeced data.
autoplot(dy)+ggtitle("Differenced Change in AUD/JPY :Forex Time Plot")+
  ylab("AUD/JPY")
```



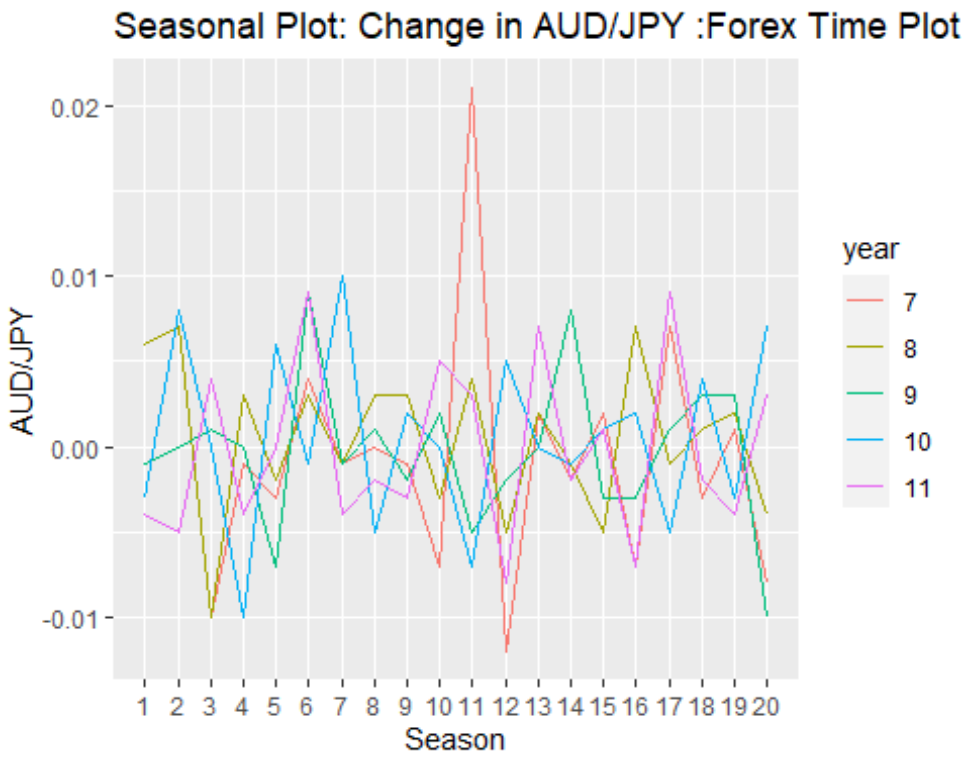
Differencing the second time to make the data stationary and remove trend

```
dy0=diff(dy)
#plotting differeced data.
autoplot(dy0)+ggtitle("Differenced2 Change in AUD/JPY :Forex Time Plot")+
  ylab("AUD/JPY")
```



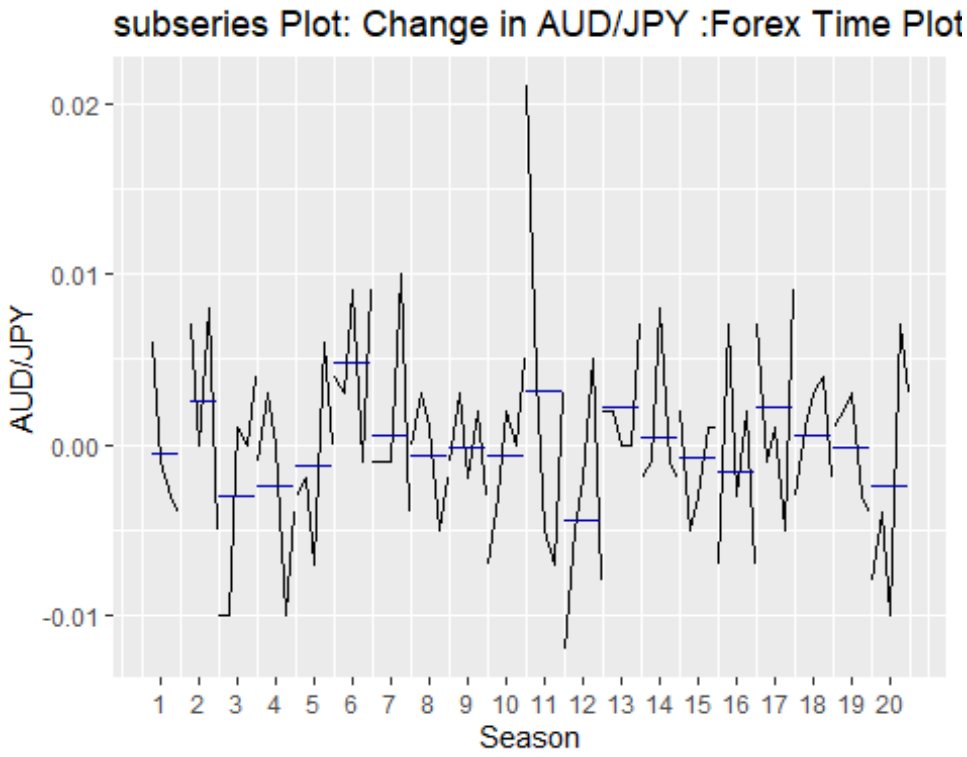
series appear trend-stationary,use to investigate seasonality.

```
ggseasonplot(dy0)+ggtitle("Seasonal Plot: Change in AUD/JPY :Forex Time
Plot")+
  ylab("AUD/JPY")
```



Another seasonal plot, the subseries plot.

```
ggsubseriesplot(dy0)+ggtitle("subseries Plot: Change in AUD/JPY :Forex Time Plot")+
 ylab("AUD/JPY")
```



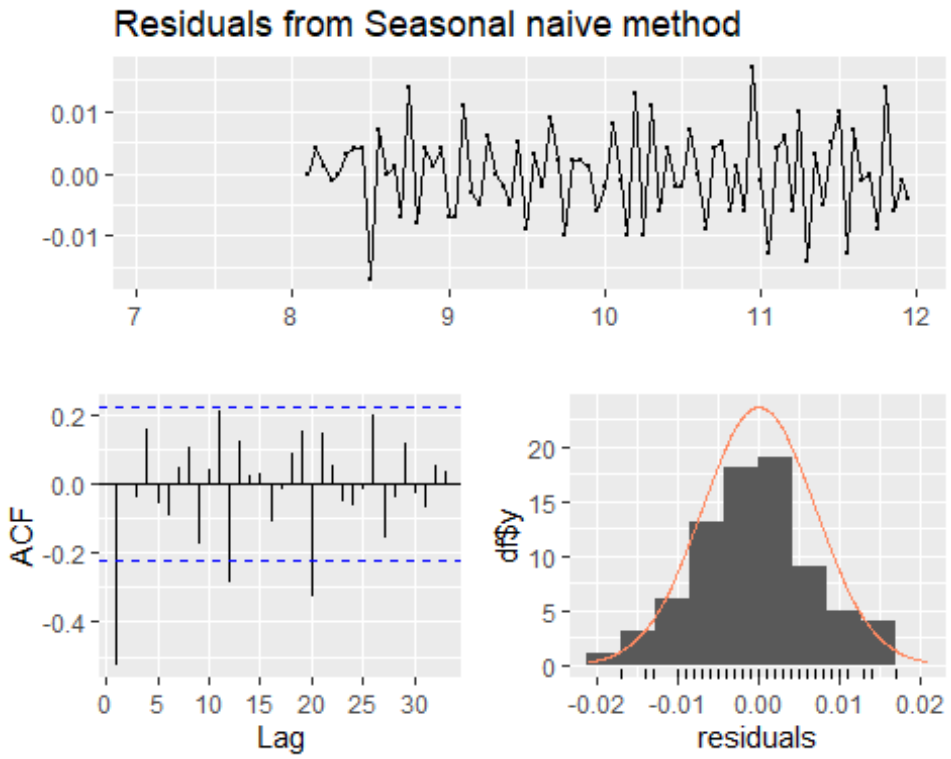

```
#**Each season requires at least 2 observations** for doing sub series plot
```

If our model has seasonality and trend we take the first difference. Forecast with various methods

use benchmark method to forecast. Using seasonal naive method as our benchmark y_t = y_(t-s)+e_t

```
fit=snaive(dy0) #residual=0.007
summary(fit)

##
## Forecast method: Seasonal naive method
##
## Model Information:
## Call: snaive(y = dy0)
##
## Residual sd: 0.007
##
## Error measures:
```

```
##                       ME        RMSE         MAE  MPE MAPE MASE
ACF1
## Training set 1.282051e-05 0.006999084 0.005551282 -Inf  Inf    1 -
0.5239652
##
## Forecasts:
##       Point Forecast         Lo 80        Hi 80        Lo 95       Hi 95
## 12.00         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.05         -0.005 -0.0139696873 0.0039696873 -0.018717953 0.008717953
## 12.10          0.004 -0.0049696873 0.0129696873 -0.009717953 0.017717953
## 12.15         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.20          0.000 -0.0089696873 0.0089696873 -0.013717953 0.013717953
## 12.25          0.009  0.0000303127 0.0179696873 -0.004717953 0.022717953
## 12.30         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.35         -0.002 -0.0109696873 0.0069696873 -0.015717953 0.011717953
## 12.40         -0.003 -0.0119696873 0.0059696873 -0.016717953 0.010717953
## 12.45          0.005 -0.0039696873 0.0139696873 -0.008717953 0.018717953
## 12.50          0.003 -0.0059696873 0.0119696873 -0.010717953 0.016717953
## 12.55         -0.008 -0.0169696873 0.0009696873 -0.021717953 0.005717953
## 12.60          0.007 -0.0019696873 0.0159696873 -0.006717953 0.020717953
## 12.65         -0.002 -0.0109696873 0.0069696873 -0.015717953 0.011717953
## 12.70          0.001 -0.0079696873 0.0099696873 -0.012717953 0.014717953
## 12.75         -0.007 -0.0159696873 0.0019696873 -0.020717953 0.006717953
## 12.80          0.009  0.0000303127 0.0179696873 -0.004717953 0.022717953
## 12.85         -0.002 -0.0109696873 0.0069696873 -0.015717953 0.011717953
## 12.90         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.95          0.003 -0.0059696873 0.0119696873 -0.010717953 0.016717953
## 13.00         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.05         -0.005 -0.0176850534 0.0076850534 -0.024400115 0.014400115
## 13.10          0.004 -0.0086850534 0.0166850534 -0.015400115 0.023400115
## 13.15         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.20          0.000 -0.0126850534 0.0126850534 -0.019400115 0.019400115
## 13.25          0.009 -0.0036850534 0.0216850534 -0.010400115 0.028400115
## 13.30         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.35         -0.002 -0.0146850534 0.0106850534 -0.021400115 0.017400115
## 13.40         -0.003 -0.0156850534 0.0096850534 -0.022400115 0.016400115
## 13.45          0.005 -0.0076850534 0.0176850534 -0.014400115 0.024400115
## 13.50          0.003 -0.0096850534 0.0156850534 -0.016400115 0.022400115
## 13.55         -0.008 -0.0206850534 0.0046850534 -0.027400115 0.011400115
## 13.60          0.007 -0.0056850534 0.0196850534 -0.012400115 0.026400115
## 13.65         -0.002 -0.0146850534 0.0106850534 -0.021400115 0.017400115
## 13.70          0.001 -0.0116850534 0.0136850534 -0.018400115 0.020400115
## 13.75         -0.007 -0.0196850534 0.0056850534 -0.026400115 0.012400115
## 13.80          0.009 -0.0036850534 0.0216850534 -0.010400115 0.028400115
## 13.85         -0.002 -0.0146850534 0.0106850534 -0.021400115 0.017400115
## 13.90         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.95          0.003 -0.0096850534 0.0156850534 -0.016400115 0.022400115

checkresiduals(fit)
```



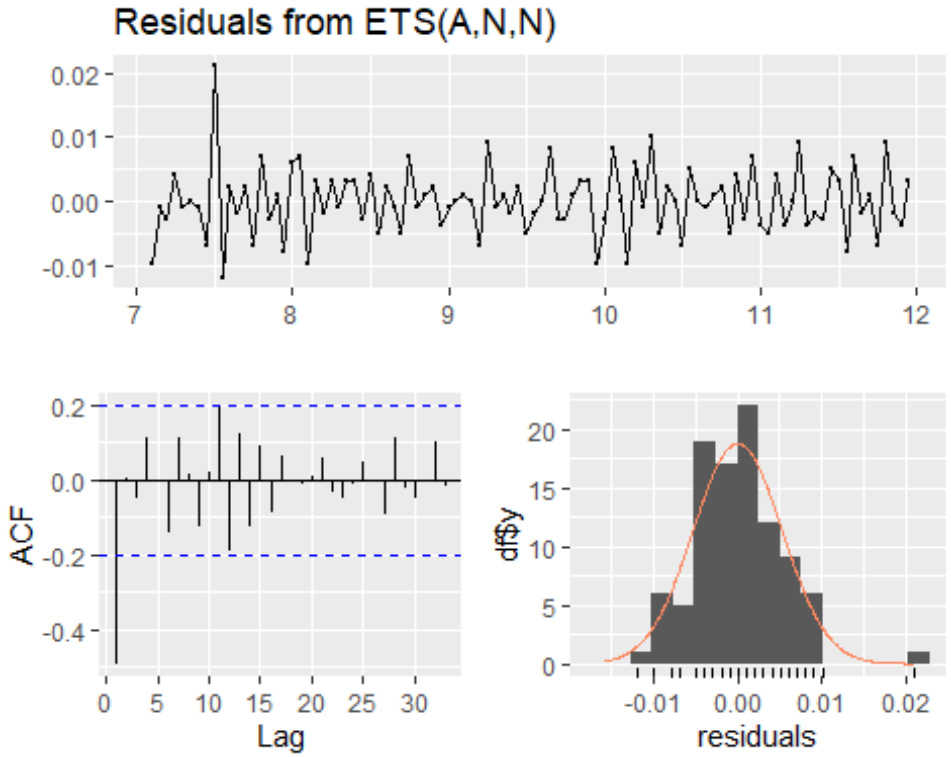

```
##
##  Ljung-Box test
##
## data:  Residuals from Seasonal naive method
## Q* = 58.972, df = 20, p-value = 1.026e-05
##
## Model df: 0.   Total lags used: 20
```

Fit exponential smoothing Fit ETS method

```
fit_ets=ets(dy0) #residual= 0.0728011
summary(fit_ets)
```

```
## ETS(A,N,N)
##
## Call:
##  ets(y = dy0)
##
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = -1e-04
##
```

```
##   sigma:  0.0053
##
##       AIC      AICc       BIC
## -573.3873 -573.1320 -565.6324
##
## Training set error measures:
##                       ME        RMSE         MAE MPE MAPE      MASE
ACF1
## Training set 1.675022e-06 0.005255177 0.004012309 Inf  Inf 0.7227716 -
0.4900633

checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(A,N,N)
## Q* = 45.615, df = 18, p-value = 0.0003375
##
## Model df: 2.   Total lags used: 20
```

fitting arima model

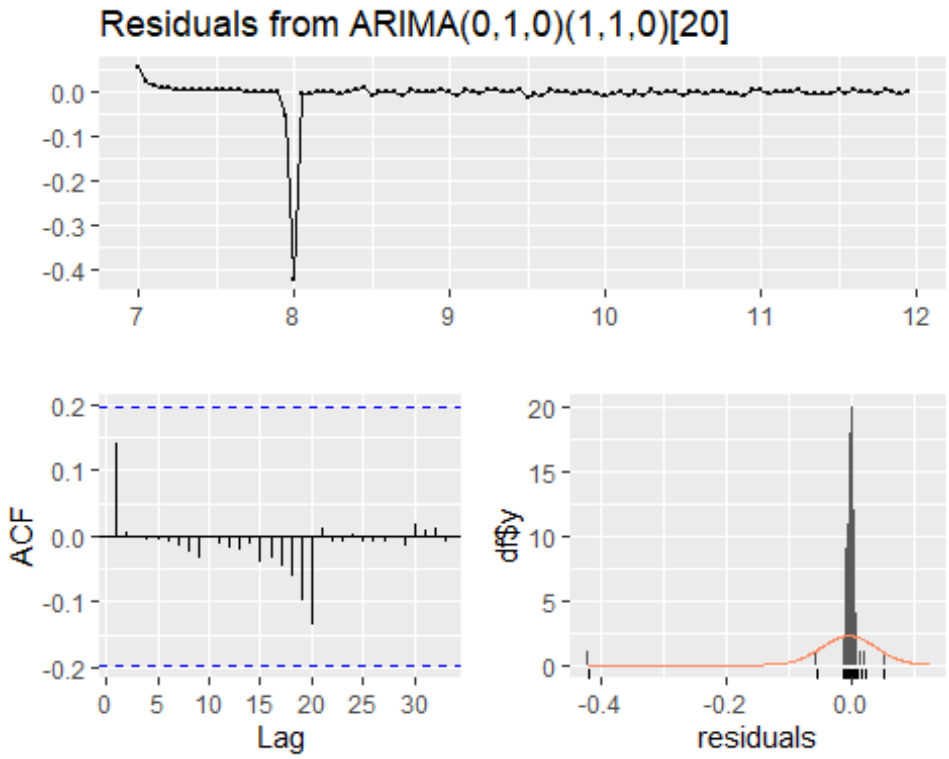
```
fit_arima=auto.arima(jpyt,d=1,D=1,stepwise = FALSE,approximation =
FALSE,trace = TRUE) #residual= 0.04872371

##
##  ARIMA(0,1,0)(0,1,0)[20]                    : -617.13
##  ARIMA(0,1,0)(0,1,1)[20]                    : -631.8449
##  ARIMA(0,1,0)(1,1,0)[20]                    : -632.9464
##  ARIMA(0,1,0)(1,1,1)[20]                    : -630.8486
##  ARIMA(0,1,1)(0,1,0)[20]                    : -615.2451
##  ARIMA(0,1,1)(0,1,1)[20]                    : -630.6738
##  ARIMA(0,1,1)(1,1,0)[20]                    : -631.6356
##  ARIMA(0,1,1)(1,1,1)[20]                    : -629.4158
##  ARIMA(0,1,2)(0,1,0)[20]                    : -613.0854
##  ARIMA(0,1,2)(0,1,1)[20]                    : -628.4624
##  ARIMA(0,1,2)(1,1,0)[20]                    : -629.4166
##  ARIMA(0,1,2)(1,1,1)[20]                    : -627.1362
##  ARIMA(0,1,3)(0,1,0)[20]                    : -611.5752
##  ARIMA(0,1,3)(0,1,1)[20]                    : -626.2083
##  ARIMA(0,1,3)(1,1,0)[20]                    : -627.3483
##  ARIMA(0,1,3)(1,1,1)[20]                    : -625.0265
##  ARIMA(0,1,4)(0,1,0)[20]                    : -612.4637
##  ARIMA(0,1,4)(0,1,1)[20]                    : -624.4351
##  ARIMA(0,1,4)(1,1,0)[20]                    : -625.4641
##  ARIMA(0,1,5)(0,1,0)[20]                    : -610.121
##  ARIMA(1,1,0)(0,1,0)[20]                    : -615.2455
##  ARIMA(1,1,0)(0,1,1)[20]                    : -630.6799
##  ARIMA(1,1,0)(1,1,0)[20]                    : -631.6431
##  ARIMA(1,1,0)(1,1,1)[20]                    : -629.4239
##  ARIMA(1,1,1)(0,1,0)[20]                    : -613.0838
##  ARIMA(1,1,1)(0,1,1)[20]                    : -628.461
##  ARIMA(1,1,1)(1,1,0)[20]                    : -629.5236
##  ARIMA(1,1,1)(1,1,1)[20]                    : -627.254
##  ARIMA(1,1,2)(0,1,0)[20]                    : -612.5305
##  ARIMA(1,1,2)(0,1,1)[20]                    : -626.592
##  ARIMA(1,1,2)(1,1,0)[20]                    : -627.2949
##  ARIMA(1,1,2)(1,1,1)[20]                    : -624.9536
##  ARIMA(1,1,3)(0,1,0)[20]                    : -611.1438
##  ARIMA(1,1,3)(0,1,1)[20]                    : -624.3759
##  ARIMA(1,1,3)(1,1,0)[20]                    : -625.2368
##  ARIMA(1,1,4)(0,1,0)[20]                    : -610.12
##  ARIMA(2,1,0)(0,1,0)[20]                    : -613.0848
##  ARIMA(2,1,0)(0,1,1)[20]                    : -628.4611
##  ARIMA(2,1,0)(1,1,0)[20]                    : -629.4244
##  ARIMA(2,1,0)(1,1,1)[20]                    : -627.1442
##  ARIMA(2,1,1)(0,1,0)[20]                    : -612.0823
##  ARIMA(2,1,1)(0,1,1)[20]                    : Inf
##  ARIMA(2,1,1)(1,1,0)[20]                    : Inf
##  ARIMA(2,1,1)(1,1,1)[20]                    : -624.9436
##  ARIMA(2,1,2)(0,1,0)[20]                    : Inf
```

```
##  ARIMA(2,1,2)(0,1,1)[20]                    : Inf
##  ARIMA(2,1,2)(1,1,0)[20]                    : Inf
##  ARIMA(2,1,3)(0,1,0)[20]                    : Inf
##  ARIMA(3,1,0)(0,1,0)[20]                    : -611.1239
##  ARIMA(3,1,0)(0,1,1)[20]                    : -626.1798
##  ARIMA(3,1,0)(1,1,0)[20]                    : -627.4687
##  ARIMA(3,1,0)(1,1,1)[20]                    : -625.1611
##  ARIMA(3,1,1)(0,1,0)[20]                    : -610.9281
##  ARIMA(3,1,1)(0,1,1)[20]                    : -624.2706
##  ARIMA(3,1,1)(1,1,0)[20]                    : -625.2446
##  ARIMA(3,1,2)(0,1,0)[20]                    : Inf
##  ARIMA(4,1,0)(0,1,0)[20]                    : -613.1485
##  ARIMA(4,1,0)(0,1,1)[20]                    : -624.4584
##  ARIMA(4,1,0)(1,1,0)[20]                    : -625.3982
##  ARIMA(4,1,1)(0,1,0)[20]                    : -610.8851
##  ARIMA(5,1,0)(0,1,0)[20]                    : -610.9229
##
##
##
##  Best model: ARIMA(0,1,0)(1,1,0)[20]
```

```
summary(fit_arima)
```

```
## Series: jpyt
## ARIMA(0,1,0)(1,1,0)[20]
##
## Coefficients:
##          sar1
##       -0.5108
## s.e.   0.1010
##
## sigma^2 = 0.002374:  log likelihood = 318.55
## AIC=-633.1   AICc=-632.95   BIC=-628.37
##
## Training set error measures:
##                        ME       RMSE         MAE         MPE        MAPE
## Training set -0.003212004 0.04302951 0.009095485 -0.00343368 0.009722312
##                   MASE      ACF1
## Training set 0.694975 0.1399099
```

```
checkresiduals(fit_arima)
```



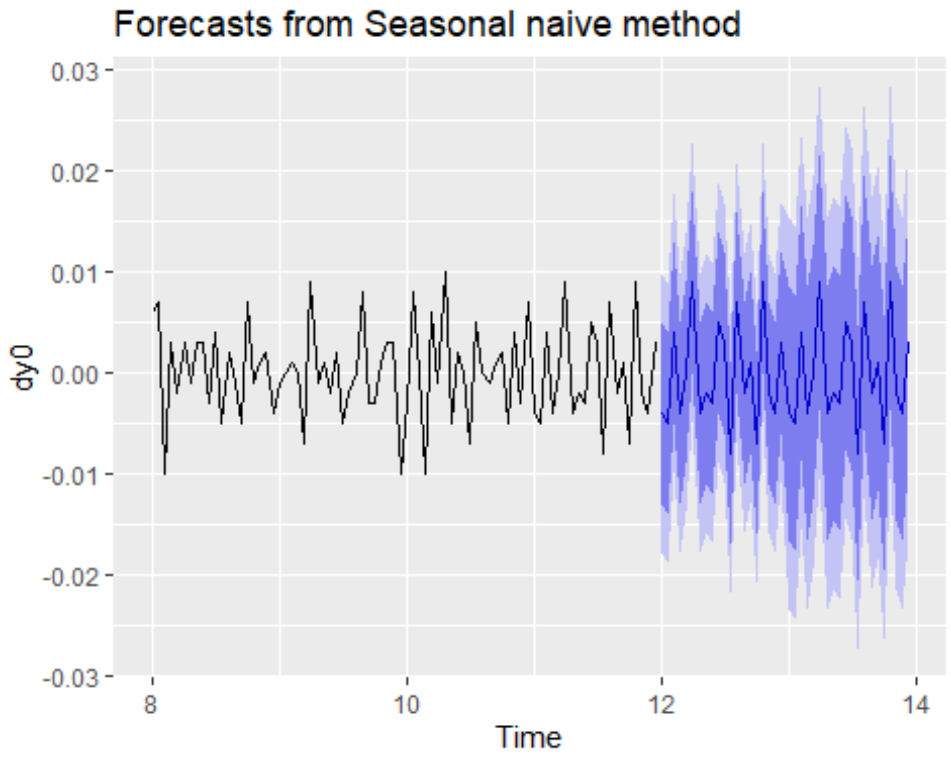

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,1,0)(1,1,0)[20]
## Q* = 7.0392, df = 19, p-value = 0.994
##
## Model df: 1.   Total lags used: 20

forecast(fit_arima)

##       Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 12.00       93.53940 93.47696 93.60184 93.44391 93.63489
## 12.05       93.53745 93.44914 93.62575 93.40240 93.67249
## 12.10       93.53745 93.42930 93.64559 93.37205 93.70284
## 12.15       93.53038 93.40550 93.65526 93.33940 93.72137
## 12.20       93.52638 93.38676 93.66600 93.31285 93.73991
## 12.25       93.52627 93.37333 93.67922 93.29237 93.76018
## 12.30       93.52932 93.36412 93.69451 93.27667 93.78196
## 12.35       93.52883 93.35222 93.70543 93.25873 93.79892
## 12.40       93.52789 93.34058 93.71521 93.24142 93.81437
## 12.45       93.52940 93.33195 93.72685 93.22743 93.83138
## 12.50       93.52881 93.32172 93.73589 93.21209 93.84552
## 12.55       93.52685 93.31055 93.74314 93.19605 93.85764
## 12.60       93.52832 93.30319 93.75344 93.18401 93.87262
## 12.65       93.52829 93.29467 93.76192 93.17100 93.88559
## 12.70       93.52927 93.28745 93.77110 93.15943 93.89911
## 12.75       93.52785 93.27809 93.77760 93.14588 93.90982
```

```
## 12.80       93.52827 93.27083 93.78572 93.13455 93.92200
## 12.85       93.52976 93.26486 93.79467 93.12462 93.93490
## 12.90       93.52776 93.25560 93.79993 93.11152 93.94400
## 12.95       93.53081 93.25157 93.81004 93.10375 93.95786
## 13.00       93.52956 93.23525 93.82387 93.07945 93.97966
## 13.05       93.52656 93.21791 93.83521 93.05452 93.99859
## 13.10       93.52656 93.20421 93.84891 93.03356 94.01955
## 13.15       93.52106 93.18556 93.85655 93.00796 94.03415
## 13.20       93.51706 93.16892 93.86520 92.98462 94.04949
## 13.25       93.51956 93.15921 93.87990 92.96846 94.07066
## 13.30       93.52156 93.14941 93.89371 92.95241 94.09071
## 13.35       93.52081 93.13722 93.90440 92.93416 94.10745
## 13.40       93.51831 93.12361 93.91300 92.91467 94.12194
## 13.45       93.51956 93.11405 93.92506 92.89939 94.13972
## 13.50       93.52131 93.10528 93.93733 92.88505 94.15756
## 13.55       93.51831 93.09202 93.94460 92.86635 94.17026
## 13.60       93.52056 93.08424 93.95687 92.85327 94.18784
## 13.65       93.52106 93.07495 93.96717 92.83879 94.20333
## 13.70       93.52256 93.06686 93.97826 92.82563 94.21949
## 13.75       93.51931 93.05422 93.98440 92.80802 94.23060
## 13.80       93.52156 93.04727 93.99585 92.79619 94.24693
## 13.85       93.52331 93.03999 94.00663 92.78413 94.26248
## 13.90       93.52131 93.02912 94.01349 92.76858 94.27404
## 13.95       93.52331 93.02242 94.02420 92.75726 94.28935
```

Forecast using seasonal naive model

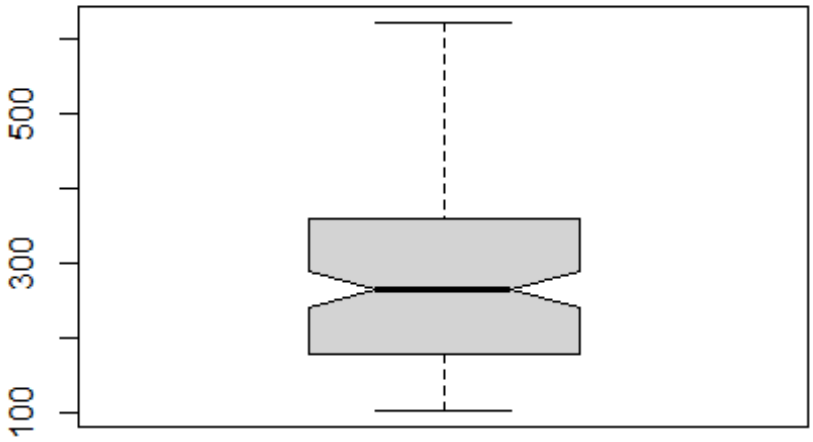
```
fcast=forecast(fit,h=40)
summary(fcast)

##
## Forecast method: Seasonal naive method
##
## Model Information:
## Call: snaive(y = dy0)
##
## Residual sd: 0.007
##
## Error measures:
##                        ME        RMSE         MAE  MPE MAPE MASE
ACF1
## Training set 1.282051e-05 0.006999084 0.005551282 -Inf  Inf    1 -
0.5239652
##
## Forecasts:
##       Point Forecast         Lo 80        Hi 80        Lo 95       Hi 95
## 12.00         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.05         -0.005 -0.0139696873 0.0039696873 -0.018717953 0.008717953
## 12.10          0.004 -0.0049696873 0.0129696873 -0.009717953 0.017717953
## 12.15         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
```

```
## 12.20          0.000 -0.0089696873 0.0089696873 -0.013717953 0.013717953
## 12.25          0.009  0.0000303127 0.0179696873 -0.004717953 0.022717953
## 12.30         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.35         -0.002 -0.0109696873 0.0069696873 -0.015717953 0.011717953
## 12.40         -0.003 -0.0119696873 0.0059696873 -0.016717953 0.010717953
## 12.45          0.005 -0.0039696873 0.0139696873 -0.008717953 0.018717953
## 12.50          0.003 -0.0059696873 0.0119696873 -0.010717953 0.016717953
## 12.55         -0.008 -0.0169696873 0.0009696873 -0.021717953 0.005717953
## 12.60          0.007 -0.0019696873 0.0159696873 -0.006717953 0.020717953
## 12.65         -0.002 -0.0109696873 0.0069696873 -0.015717953 0.011717953
## 12.70          0.001 -0.0079696873 0.0099696873 -0.012717953 0.014717953
## 12.75         -0.007 -0.0159696873 0.0019696873 -0.020717953 0.006717953
## 12.80          0.009  0.0000303127 0.0179696873 -0.004717953 0.022717953
## 12.85         -0.002 -0.0109696873 0.0069696873 -0.015717953 0.011717953
## 12.90         -0.004 -0.0129696873 0.0049696873 -0.017717953 0.009717953
## 12.95          0.003 -0.0059696873 0.0119696873 -0.010717953 0.016717953
## 13.00         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.05         -0.005 -0.0176850534 0.0076850534 -0.024400115 0.014400115
## 13.10          0.004 -0.0086850534 0.0166850534 -0.015400115 0.023400115
## 13.15         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.20          0.000 -0.0126850534 0.0126850534 -0.019400115 0.019400115
## 13.25          0.009 -0.0036850534 0.0216850534 -0.010400115 0.028400115
## 13.30         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.35         -0.002 -0.0146850534 0.0106850534 -0.021400115 0.017400115
## 13.40         -0.003 -0.0156850534 0.0096850534 -0.022400115 0.016400115
## 13.45          0.005 -0.0076850534 0.0176850534 -0.014400115 0.024400115
## 13.50          0.003 -0.0096850534 0.0156850534 -0.016400115 0.022400115
## 13.55         -0.008 -0.0206850534 0.0046850534 -0.027400115 0.011400115
## 13.60          0.007 -0.0056850534 0.0196850534 -0.012400115 0.026400115
## 13.65         -0.002 -0.0146850534 0.0106850534 -0.021400115 0.017400115
## 13.70          0.001 -0.0116850534 0.0136850534 -0.018400115 0.020400115
## 13.75         -0.007 -0.0196850534 0.0056850534 -0.026400115 0.012400115
## 13.80          0.009 -0.0036850534 0.0216850534 -0.010400115 0.028400115
## 13.85         -0.002 -0.0146850534 0.0106850534 -0.021400115 0.017400115
## 13.90         -0.004 -0.0166850534 0.0086850534 -0.023400115 0.015400115
## 13.95          0.003 -0.0096850534 0.0156850534 -0.016400115 0.022400115

autoplot(fcast,include = 80)
```



Time series data from R- airpassengers.

```
ps=AirPassengers
class(ps)

## [1] "ts"

boxplot(ps,notch = TRUE)
```


500
300
100