Simple Time Series Analysis Example

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Introduction

Simple Analysis of the AirPassengers dataset in R. AirPassengers is available by default in R.

```
library(IRdisplay)
library(magrittr)
library(scales)
library(gridExtra)
library(forecast)
```

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

```
library(tseries)
library(ggthemes)
library(ggplot2)
```

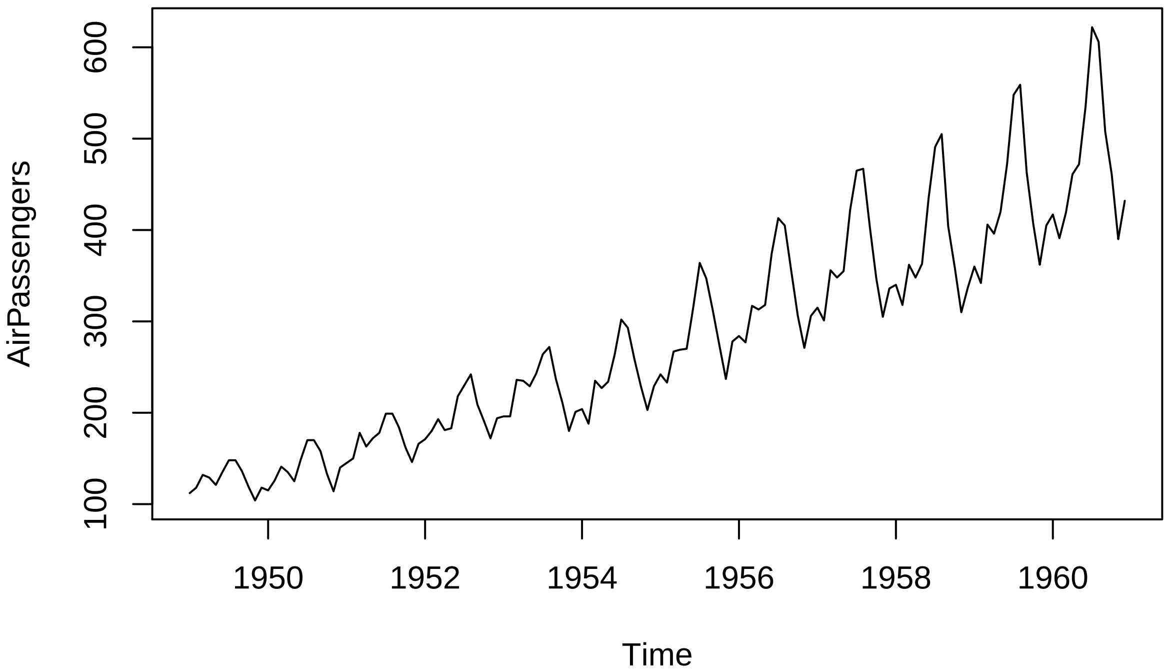
Load the data

```
data(AirPassengers)
head(AirPassengers);dim(AirPassengers)
```

```
##      Jan Feb Mar Apr May Jun
## 1949 112 118 132 129 121 135
```

```
## NULL
```

```
plot(AirPassengers)
```

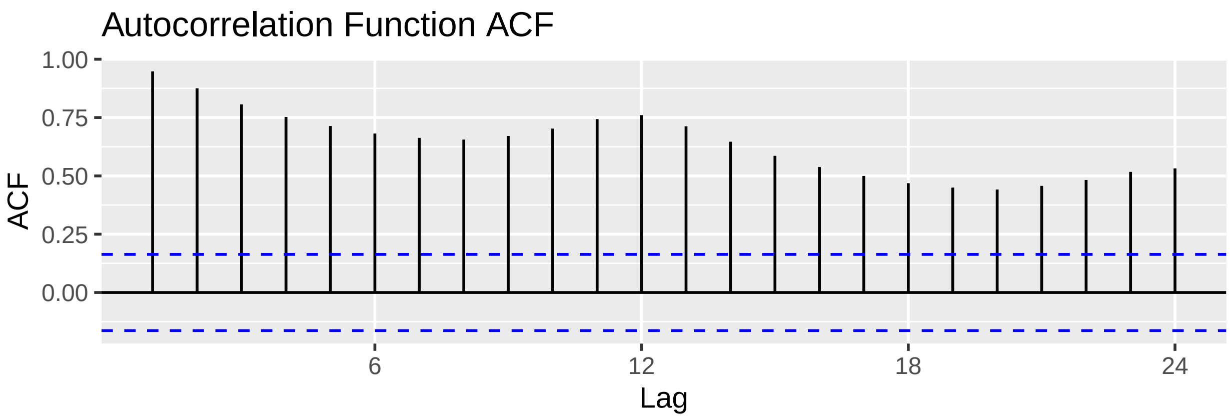


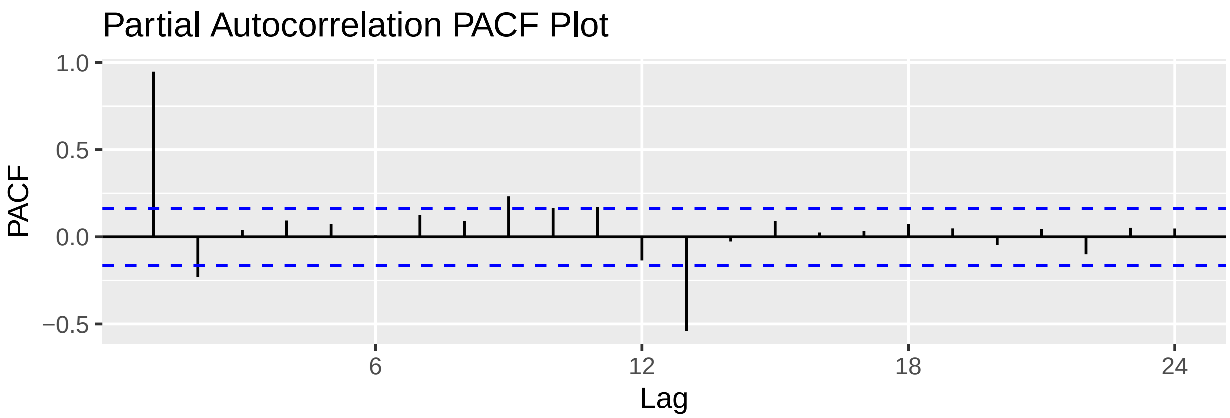
Note that the Plot shows a definite cyclycal pattern

Check for Stationarity

Option 1: Use ACF Plots

```
g1 <- ggAcf(AirPassengers,type="correlation") + ggtitle("Autocorrelation Function ACF") + xlab("Lag") +
g2 <- ggAcf(AirPassengers,type="partial") + ggtitle("Partial Autocorrelation PACF Plot")  + xlab("Lag")
grid.arrange(g1,g2)
```





Option 2: Use Augmented Dickie Fuller Test

```
adf.test(AirPassengers)
```

```
## Warning in adf.test(AirPassengers): p-value smaller than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  AirPassengers
## Dickey-Fuller = -7.3186, Lag order = 5, p-value = 0.01
## alternative hypothesis: stationary
```

Note a p-value of 0.01 indicates we REJECT the NULL Hypothesis that the data is Non-Stationary.

I.E. (double negatives!!!) - the data is STATIONARY

Fitting models

Will try 3 models ARMA, ARIMA and STL. Expecting that the ARIMA model will not do so well - since the data is Stationary, theoretically no Differencing should be needed. Interested to see how STL stacks up with ARMA

```
#fit ARMA model
arma.model <- auto.arima(AirPassengers, max.d=0)
arma.model
```

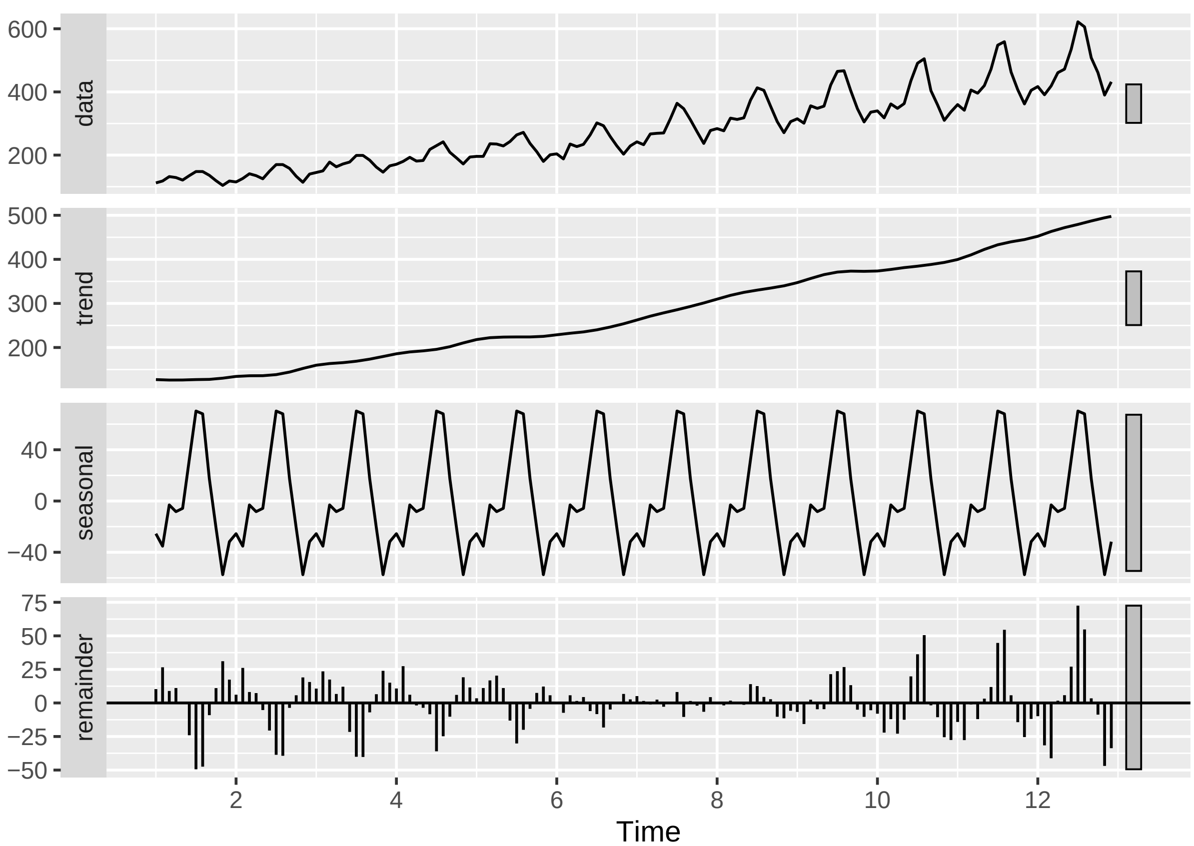
```
## Series: AirPassengers
## ARIMA(2,0,0)(0,1,0)[12] with drift
##
## Coefficients:
```

```
##          ar1     ar2   drift
##       0.5967  0.2130  2.5439
## s.e.  0.0847  0.0852  0.4152
##
## sigma^2 estimated as 130.1:  log likelihood=-507.58
## AIC=1023.16   AICc=1023.47   BIC=1034.69
```

```
#fit ARIMA model
arima.model <- auto.arima(AirPassengers)
arima.model
```

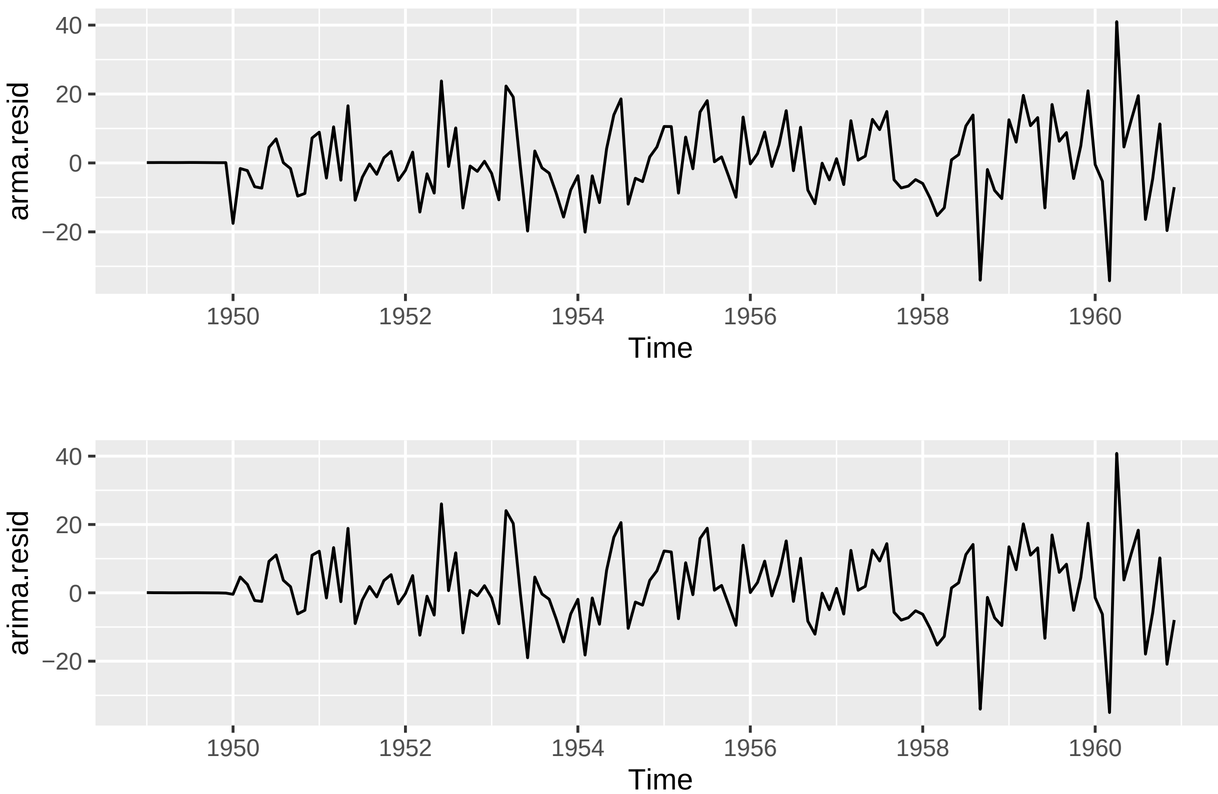
```
## Series: AirPassengers
## ARIMA(2,1,1)(0,1,0)[12]
##
## Coefficients:
##          ar1     ar2      ma1
##       0.5960  0.2143  -0.9819
## s.e.  0.0888  0.0880   0.0292
##
## sigma^2 estimated as 132.3:  log likelihood=-504.92
## AIC=1017.85   AICc=1018.17   BIC=1029.35
```

```
#fit STL model
  #1 - first transform the data to a time series
ap.ts <- ts(AirPassengers,frequency=12)

  #2 - fit a model
stl.model <- stl(ap.ts,s.window="periodic")
autoplot(stl.model)
```



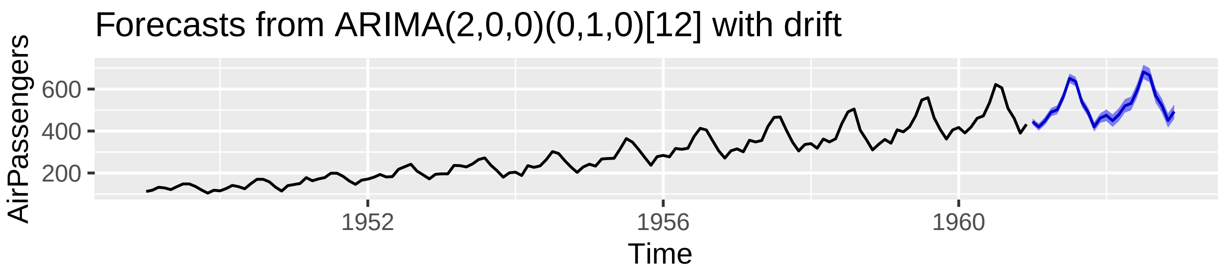
Plot residuals for ARMA and ARIMA model

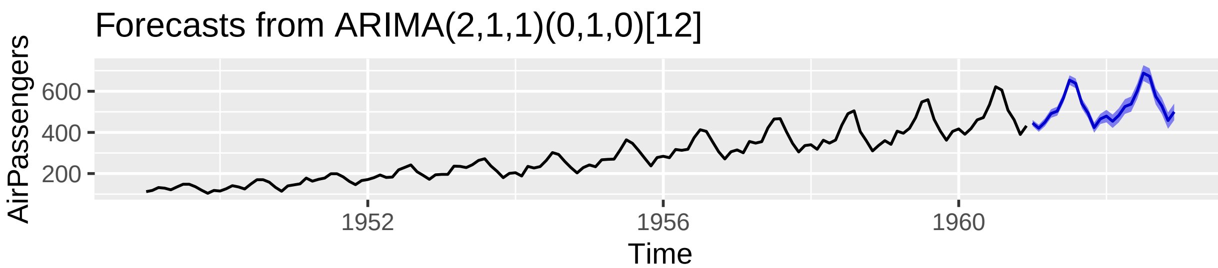
```
arma.resid <- resid(arma.model)
arima.resid <- resid(arima.model)


g1 <- autoplot(arma.resid)
g2 <- autoplot(arima.resid)
grid.arrange(g1,g2)
```

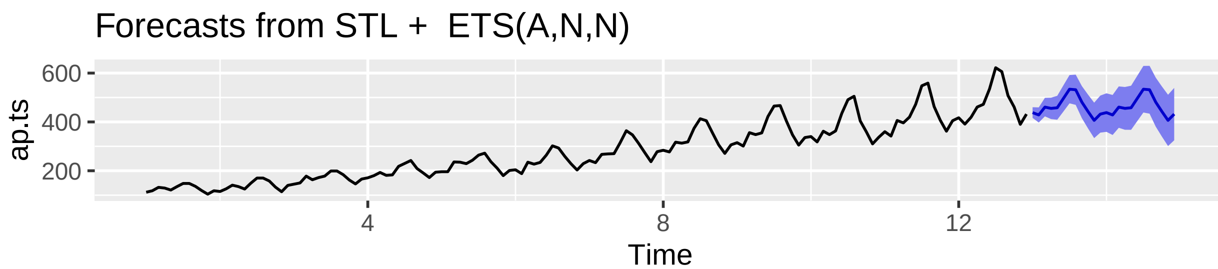


Compare the forecasts of each model

```
#forecasting for 2 years. 80% confidence
arma.forecast <- forecast(arma.model,h=24,level=80)
arima.forecast <- forecast(arima.model,h=24,level=80)
stl.forecast <- forecast(stl.model, h=24, level=80)

g1 <- autoplot(arma.forecast)
g2 <- autoplot(arima.forecast)
g3 <- autoplot(stl.forecast)
grid.arrange(g1,g2,g3)
```







Conclusion No difference between the ARMA and ARIMA Models (expected as the data is stationary) STL performed poorer that I had expected