

# BF HW3

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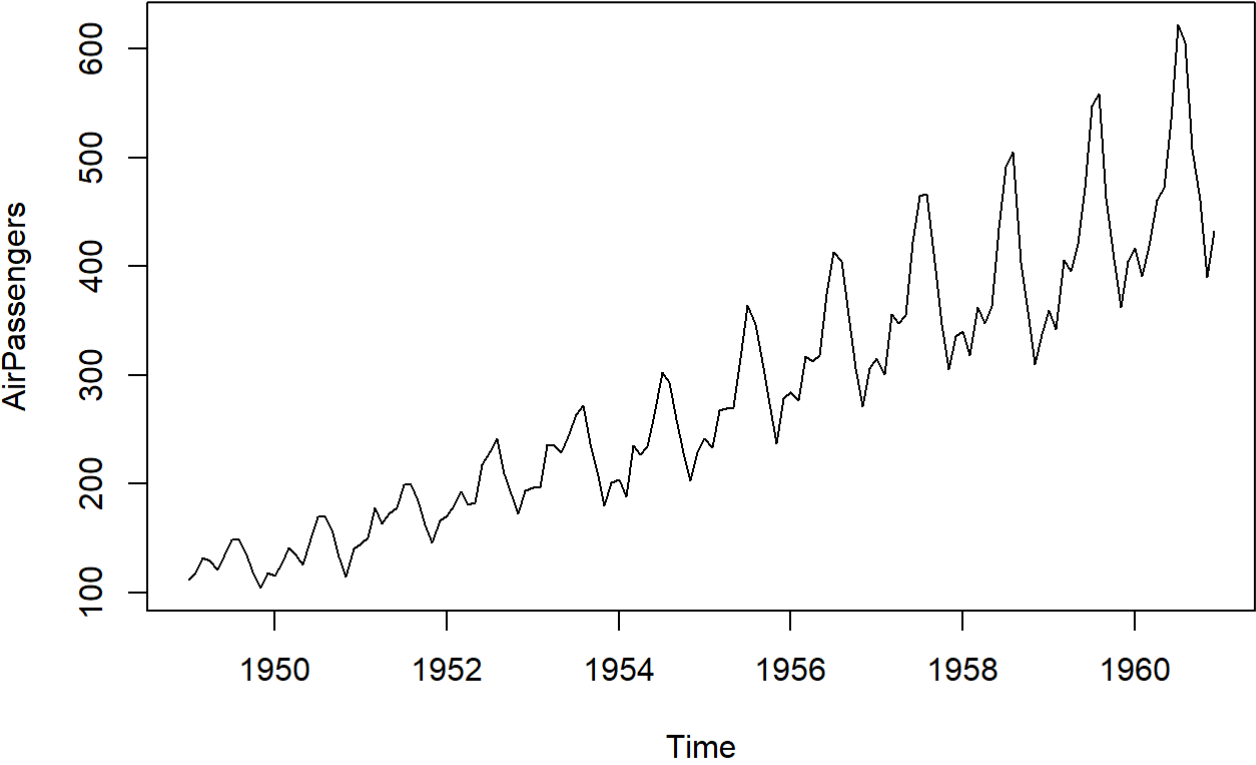
9/25/2022

AirPassengers

```
##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 1949 112 118 132 129 121 135 148 148 136 119 104 118
## 1950 115 126 141 135 125 149 170 170 158 133 114 140
## 1951 145 150 178 163 172 178 199 199 184 162 146 166
## 1952 171 180 193 181 183 218 230 242 209 191 172 194
## 1953 196 196 236 235 229 243 264 272 237 211 180 201
## 1954 204 188 235 227 234 264 302 293 259 229 203 229
## 1955 242 233 267 269 270 315 364 347 312 274 237 278
## 1956 284 277 317 313 318 374 413 405 355 306 271 306
## 1957 315 301 356 348 355 422 465 467 404 347 305 336
## 1958 340 318 362 348 363 435 491 505 404 359 310 337
## 1959 360 342 406 396 420 472 548 559 463 407 362 405
## 1960 417 391 419 461 472 535 622 606 508 461 390 432
```

```
## The data describes the number of monthly Air passengers from 1949 to 1960

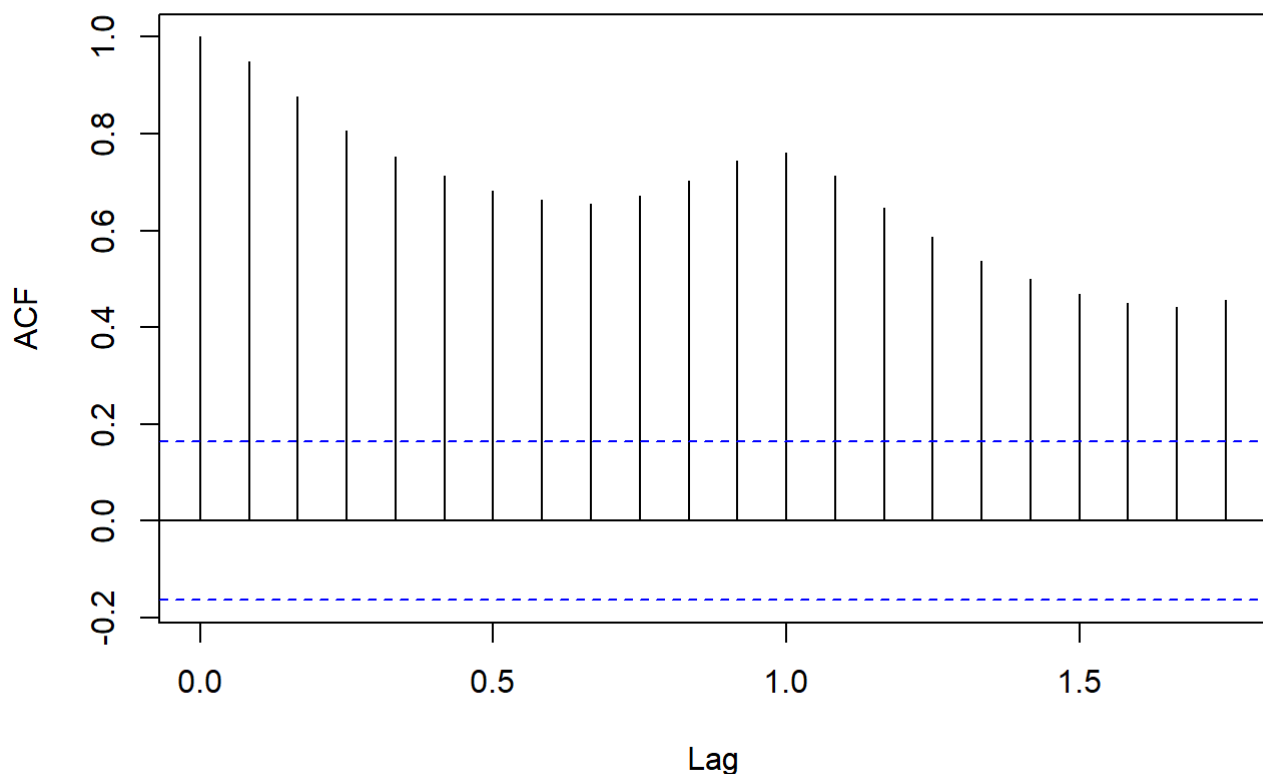
#Plot
plot(AirPassengers)
```



## The plot depicts the upward trend and seasonality where it analyzed in the given data. It shows a positive trend growth. By analyzing the plot graph, as there is trending the first value in the ACF will be a strong correlation as the first 2 points are near. Then the next values in ACF will be slightly weaker than the previous points as the lag between the points in the plot is far. As there is seasonality in the plot, the autocorrelation values will be correlated with the 1st, 4th and 8th lag and so on where they will be slightly weaker than the previous lags. Since as per the plot it has both seasonality and trending, the ACF shows both combination of the 2 effects mentioned.

```
#ACF
acf(AirPassengers)
```

### Series AirPassengers



## The ACF Plot describes the effect where it has both trend and seasonality. If the spike is outside the blue dash line it is statistically significant and if it is inside the blue dash line it is statistically insignificant. By analyzing the ACF plot we can conclude that all the spikes are outside the blue line and it is statistically significant.

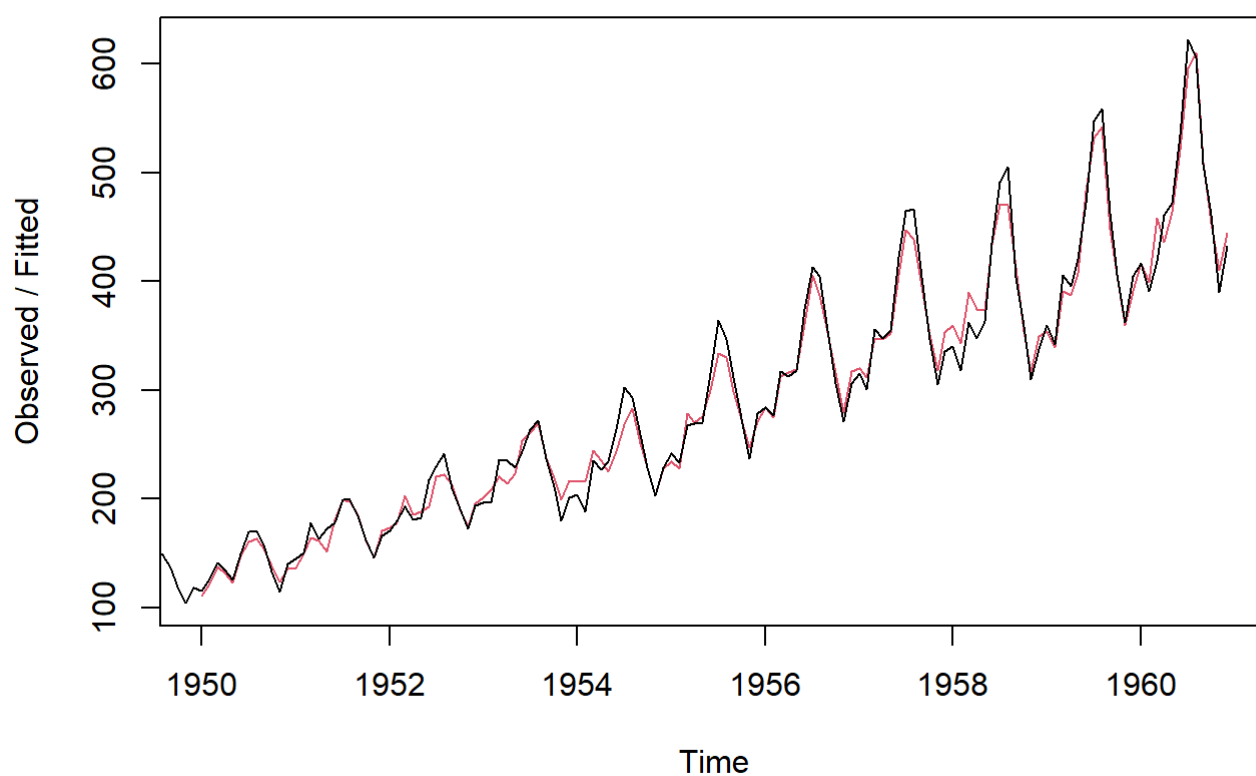
```
#HoltWinters
tmp <- HoltWinters(AirPassengers)
attributes(tmp)
```

```
## $names
## [1] "fitted"      "x"          "alpha"      "beta"      "gamma"
## [6] "coefficients" "seasonal"   "SSE"        "call"
##
## $class
## [1] "HoltWinters"
```

```
plot(tmp)
tmp_f <- forecast::forecast(tmp)
```

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

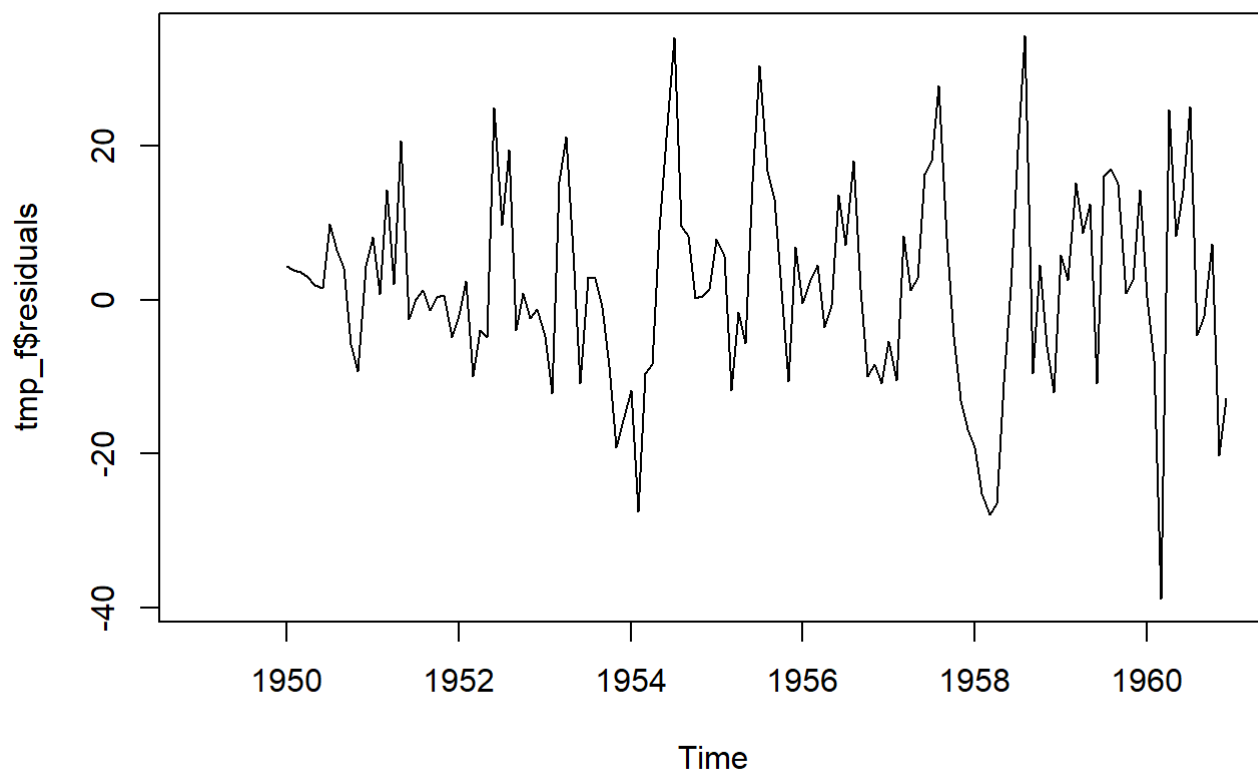
## Holt-Winters filtering



```
attributes(tmp_f)
```

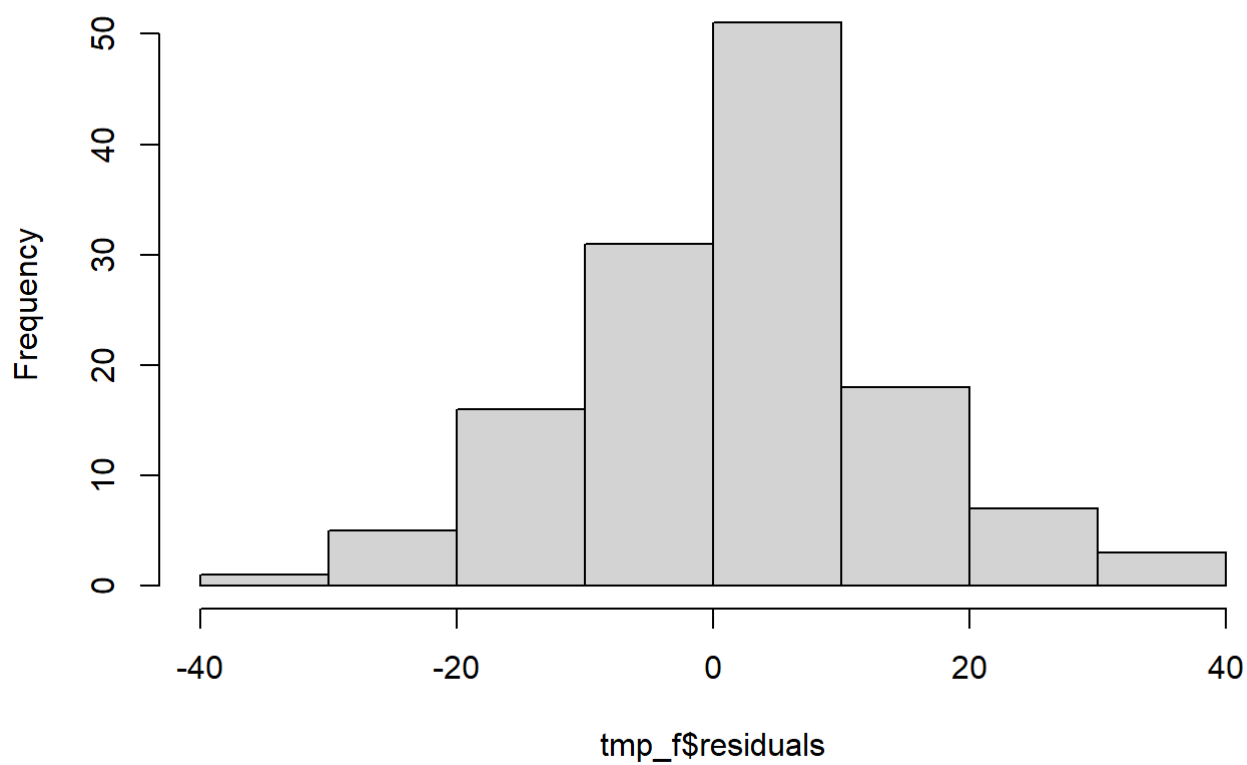
```
## $names
## [1] "method"      "model"      "level"      "mean"      "lower"      "upper"
## [7] "x"          "series"     "fitted"     "residuals"
##
## $class
## [1] "forecast"
```

```
plot(tmp_f$residuals)
```



```
hist(tmp_f$residuals)
```

**Histogram of tmp\_f\$residuals**



```
##accuracy(tmp_f)
      #ME      RMSE      MAE
#Training set 1.753445 12.86886 9.774438
      # MPE      MAPE      MASE
#Training set 0.3992849 3.400129 0.3051622
      #ACF1
#Training set 0.424139

#Window
foo <- window(AirPassengers,1953)
foo <- window(AirPassengers,1959)
plot(foo)
```



```
acf(foo)
```

Series foo

