

# hw4

Haoyu(Michael)\_Wang

2022-09-28

**package loading** We are still using UKgas data set from hw3.

```
library(fpp)
```

```
## Warning: package 'fpp' was built under R version 4.1.3
## Loading required package: forecast
## Registered S3 method overwritten by 'quantmod':
##   method             from
##   as.zoo.data.frame zoo
## Loading required package: fma
## Warning: package 'fma' was built under R version 4.1.3
## Loading required package: expsmoother
## Warning: package 'expsmooth' was built under R version 4.1.3
## Loading required package: lmtest
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric
## Loading required package: tseries
```

```
library(fpp2)
```

```
## Warning: package 'fpp2' was built under R version 4.1.3
## -- Attaching packages ----- fpp2 2.4 --
## v ggplot2 3.3.5
##
##
## Attaching package: 'fpp2'
## The following objects are masked from 'package:fpp':
##
##   ausair, ausbeer, austa, austourists, debitcards, departures,
##   elecequip, euretail, guinearice, oil, sunspotarea, usmelec
```

```
library(TTR)
```

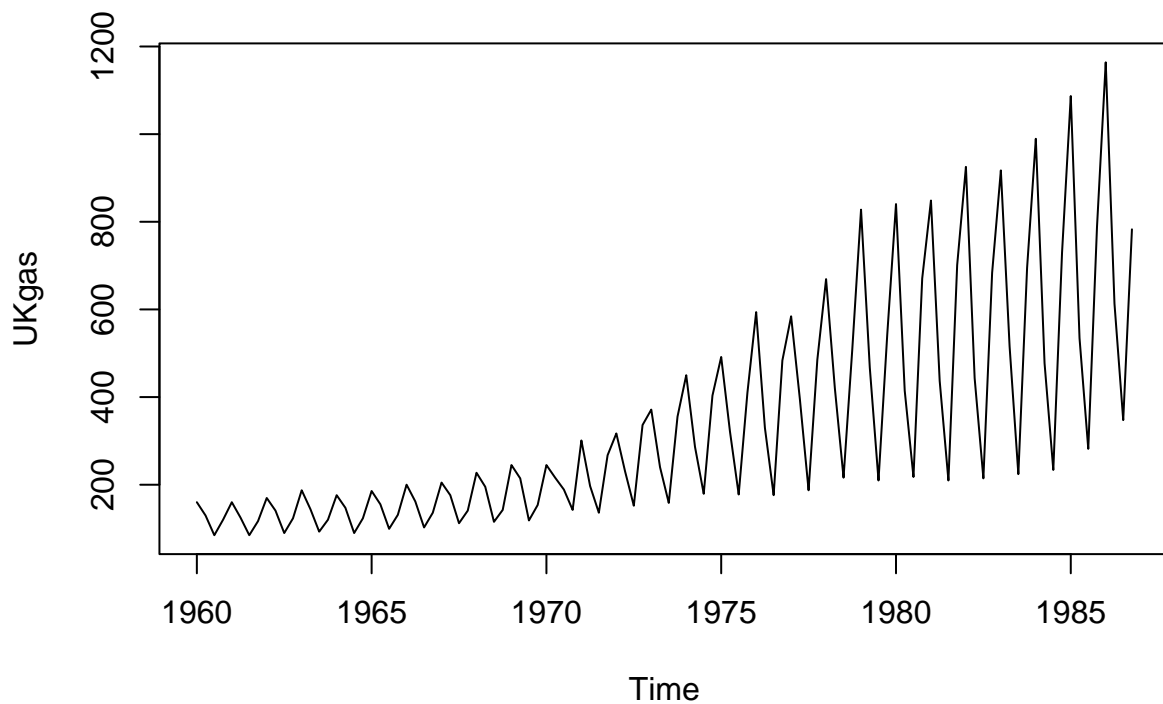
```
## Warning: package 'TTR' was built under R version 4.1.3
```

Attribute shows that it is a TS data from 1960 - 1986, the plot of UKgas showing a growing trend and increase over time means that we can use the whole data set instead shorten its periodicity. The acf shows a huge seasonality possibility. So how should we properly predict the values in the future?

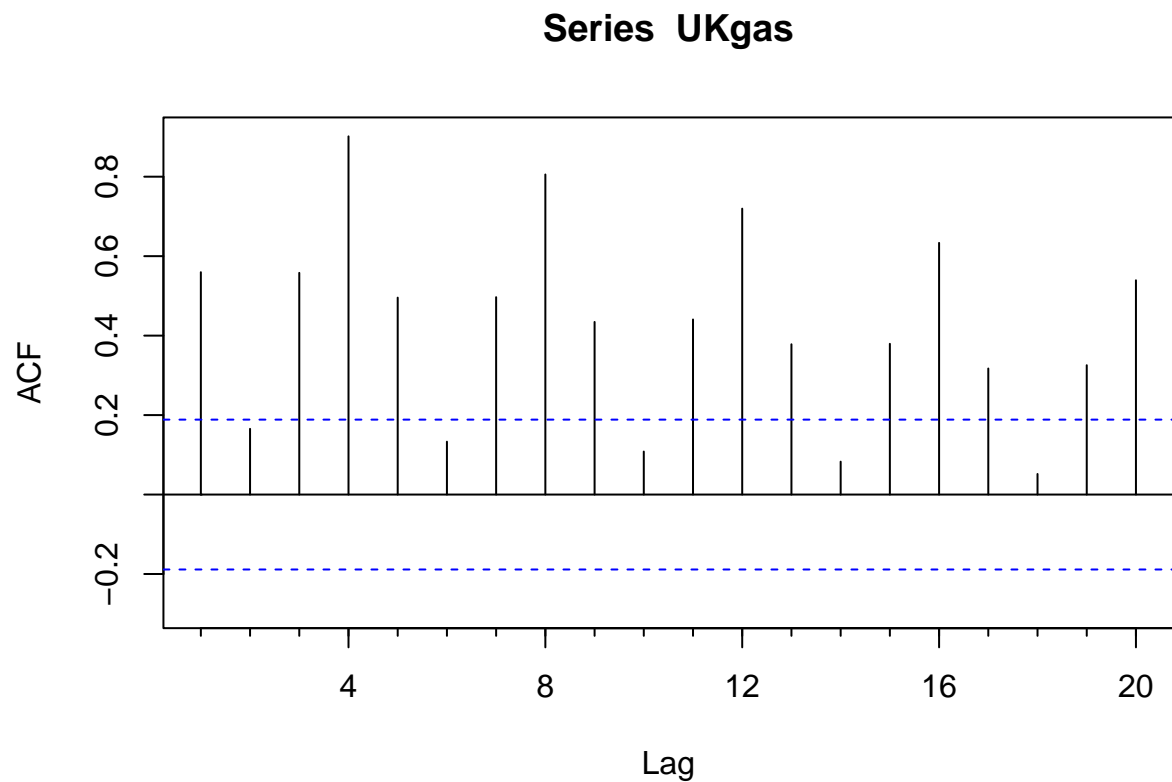
```
attributes(UKgas)
```

```
## $tsp  
## [1] 1960.00 1986.75    4.00  
##  
## $class  
## [1] "ts"
```

```
plot(UKgas)
```



```
Acf(UKgas)
```



**Basic mean.** In here, since the data is quarterly recorded and the atf shows a huge coefficient at 4, I think we should use  $h=4$  to `meanf()` it.

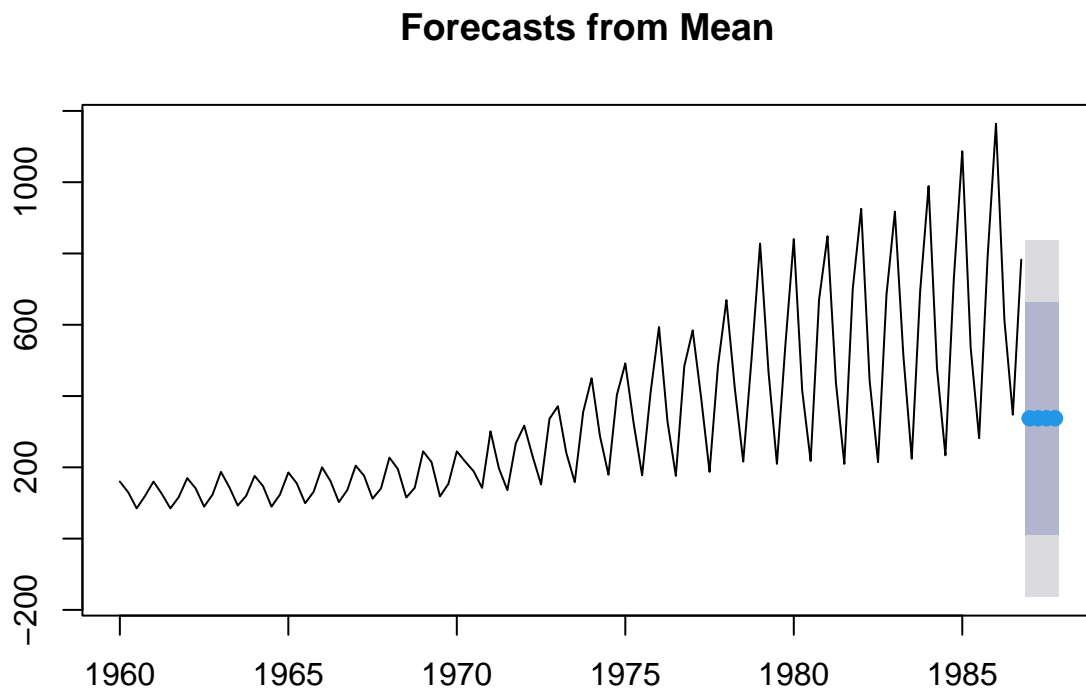
UKgas

##	Qtr1	Qtr2	Qtr3	Qtr4
## 1960	160.1	129.7	84.8	120.1
## 1961	160.1	124.9	84.8	116.9
## 1962	169.7	140.9	89.7	123.3
## 1963	187.3	144.1	92.9	120.1
## 1964	176.1	147.3	89.7	123.3
## 1965	185.7	155.3	99.3	131.3
## 1966	200.1	161.7	102.5	136.1
## 1967	204.9	176.1	112.1	140.9
## 1968	227.3	195.3	115.3	142.5
## 1969	244.9	214.5	118.5	153.7
## 1970	244.9	216.1	188.9	142.5
## 1971	301.0	196.9	136.1	267.3
## 1972	317.0	230.5	152.1	336.2
## 1973	371.4	240.1	158.5	355.4
## 1974	449.9	286.6	179.3	403.4
## 1975	491.5	321.8	177.7	409.8
## 1976	593.9	329.8	176.1	483.5
## 1977	584.3	395.4	187.3	485.1
## 1978	669.2	421.0	216.1	509.1
## 1979	827.7	467.5	209.7	542.7

```
## 1980 840.5 414.6 217.7 670.8
## 1981 848.5 437.0 209.7 701.2
## 1982 925.3 443.4 214.5 683.6
## 1983 917.3 515.5 224.1 694.8
## 1984 989.4 477.1 233.7 730.0
## 1985 1087.0 534.7 281.8 787.6
## 1986 1163.9 613.1 347.4 782.8
```

```
meanUKgas <- meanf(UKgas,4)
```

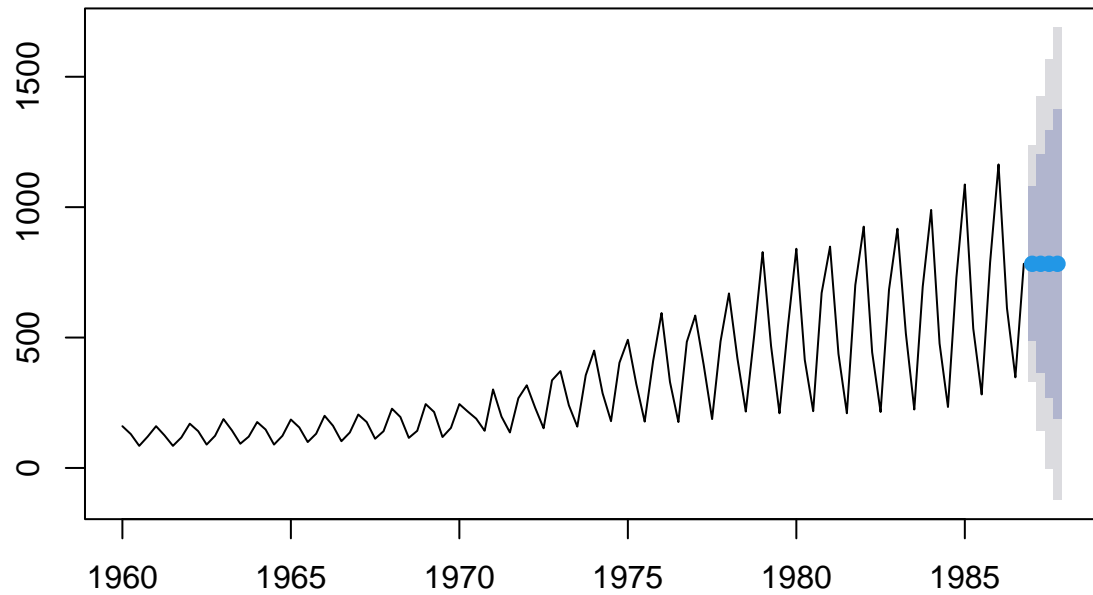
```
plot(meanUKgas)
```



```
naiveUKgas <- naive(UKgas,4)
```

```
plot(naiveUKgas)
```

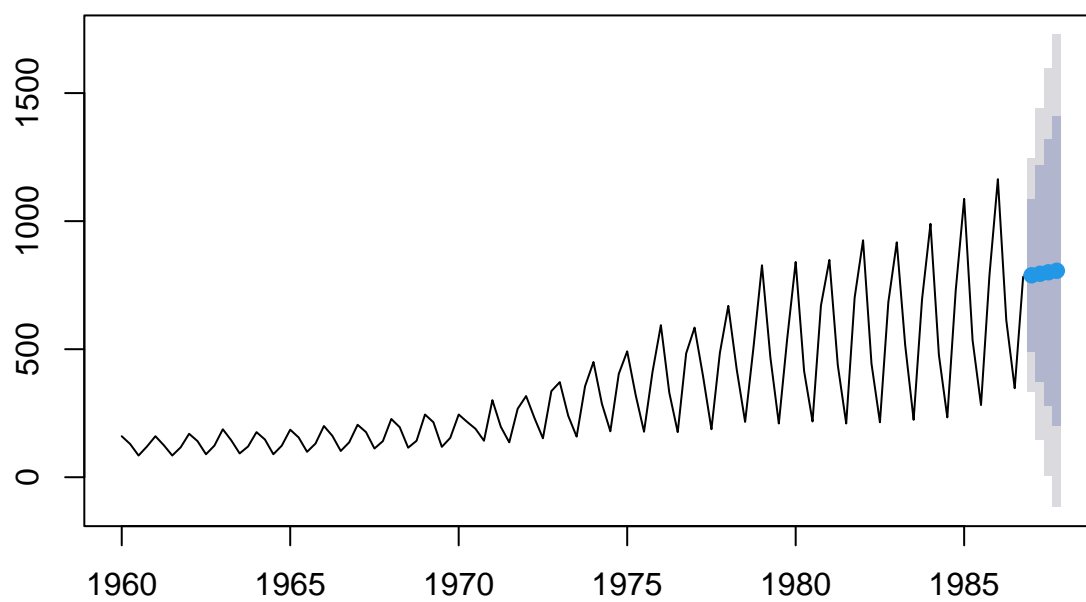
## Forecasts from Naive method



Naive

```
rwfUKgas <- rwf(UKgas,4)
rwfUKgas <- rwf(UKgas,4, drift=TRUE)
#A variation on the naive method is to allow the forecasts to increase or decrease over time, where the
rwfUKgasDriftOff <- rwf(UKgas,4, drift=FALSE)
plot(rwfUKgas)
```

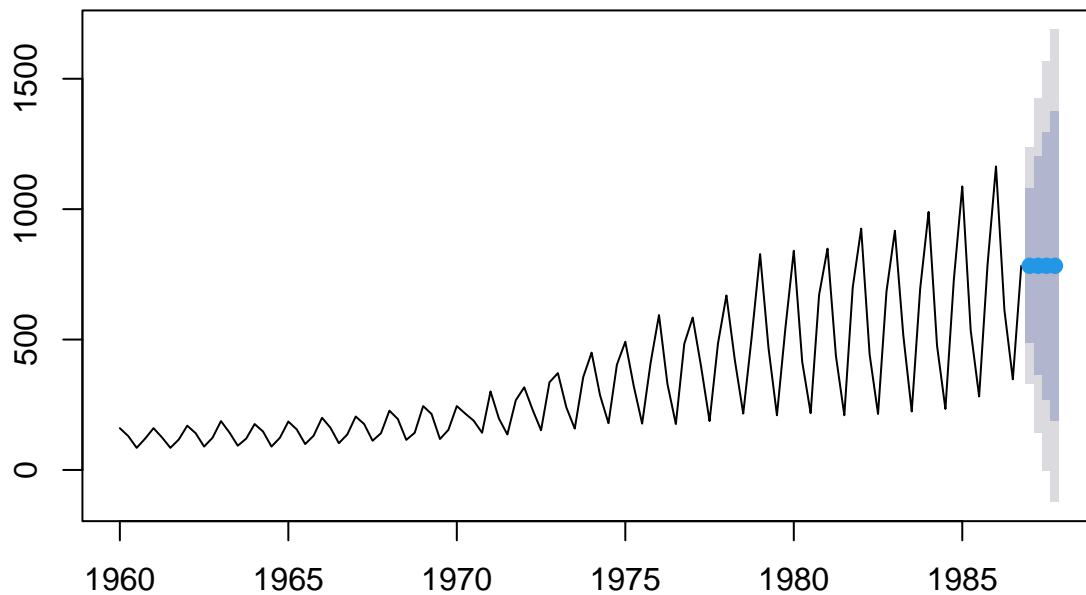
## Forecasts from Random walk with drift



random walk

```
plot(rwfUKgasDriftOff)
```

## Forecasts from Random walk



*#Here we can see that the prediction when drift off is completely flat.*

```
snaiveUKgas <- snaive(UKgas,4)
```

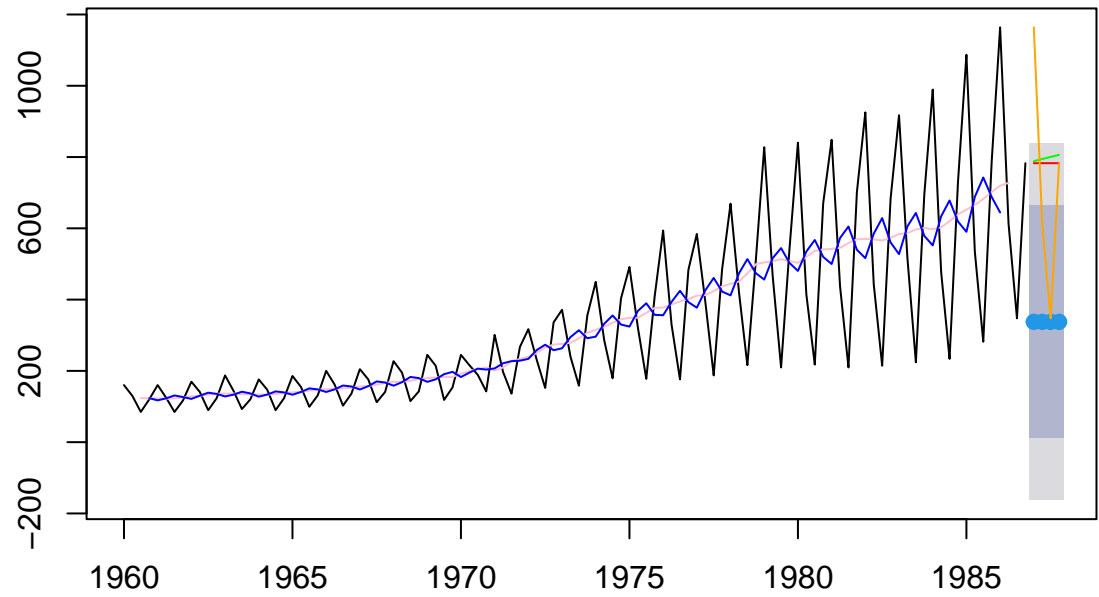
### Seasonal Naive

```
fourMAUKgas <- ma(UKgas,order=4)  
sevenMAUKgas <- ma(UKgas,order=7)
```

### Moving Average

```
plot(meanUKgas)  
lines(naiveUKgas$mean,col="red")  
lines(rwfUKgas$mean,col="green")  
lines(snaiveUKgas$mean,col="orange")  
lines(fourMAUKgas,col="Pink")  
lines(sevenMAUKgas,col="Blue")
```

## Forecasts from Mean

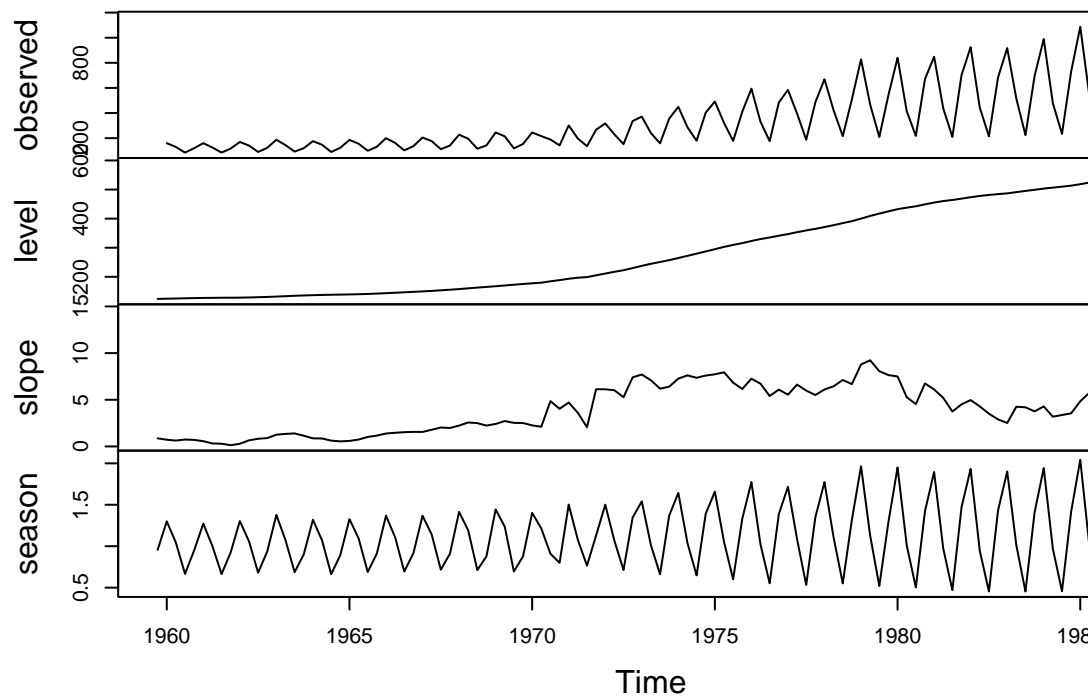


## Plotting everything

```
etsUKgas <- ets(UKgas)
plot(etsUKgas)
```



## Decomposition by ETS(M,A,M) method



Tearing apart the graph.

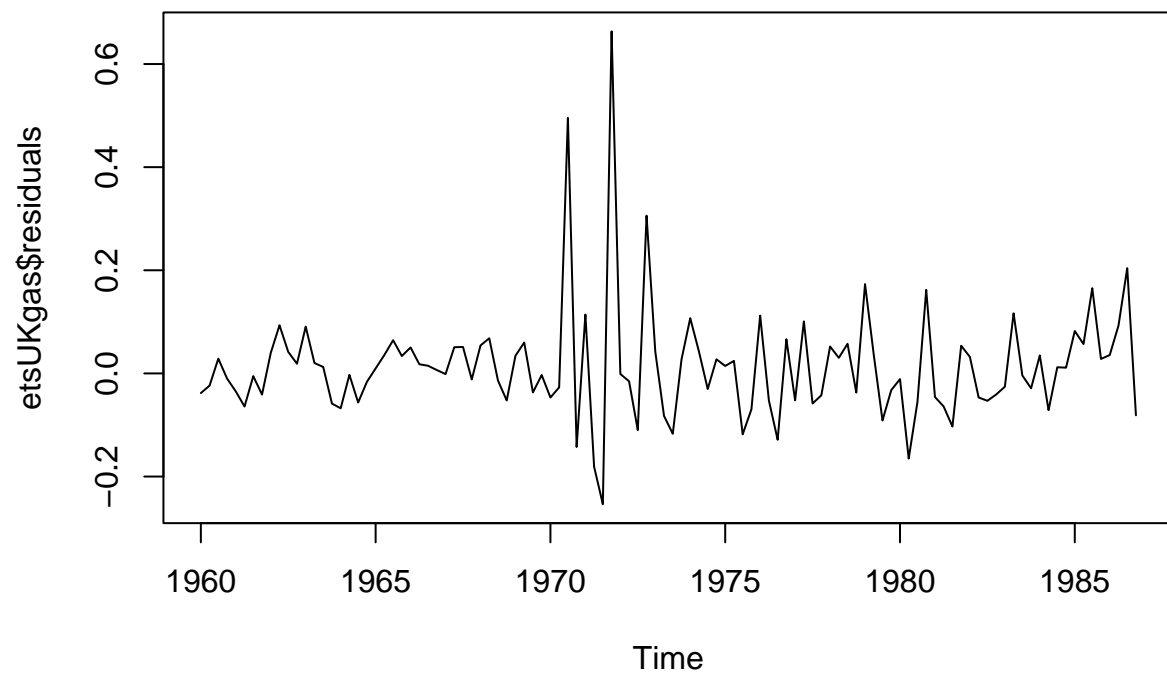
```
attributes(etsUKgas)
```

```
## $names
## [1] "loglik"      "aic"         "bic"         "aicc"        "mse"
## [6] "amse"       "fit"         "residuals"   "fitted"      "states"
## [11] "par"        "m"           "method"      "series"      "components"
## [16] "call"       "initstate"   "sigma2"      "x"
##
## $class
## [1] "ets"
```

```
#showing mse
etsUKgas$mse
```

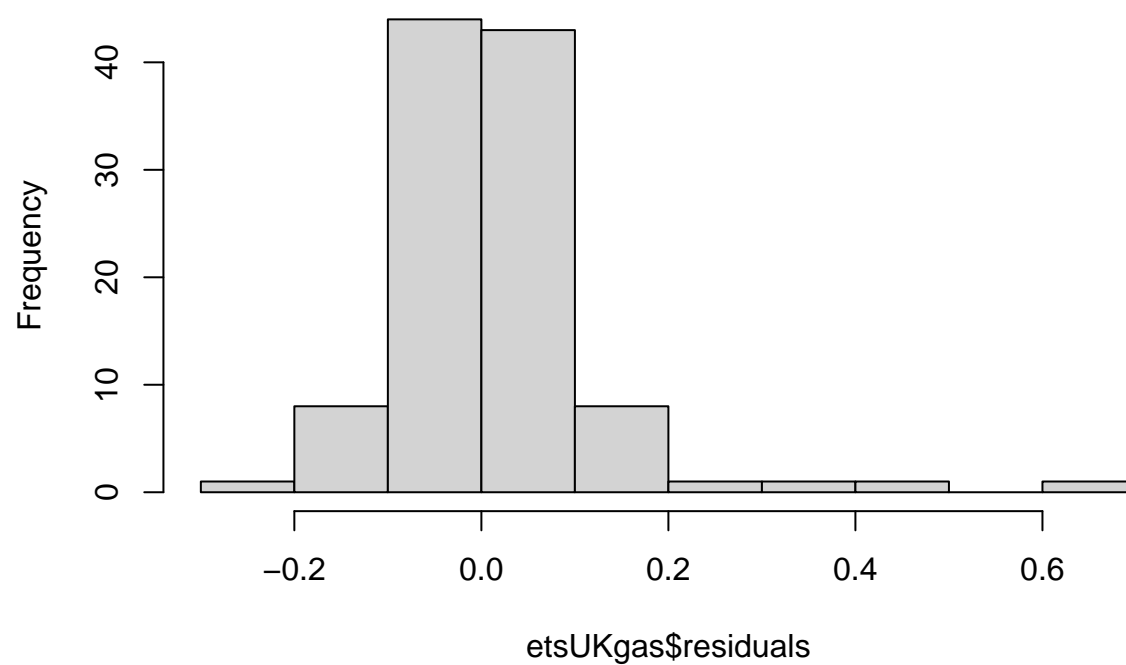
```
## [1] 1034.411
```

```
#We can see that the mean is not around 0 and right skewed. Errors are high around 1970s, probably caus
plot(etsUKgas$residuals)
```



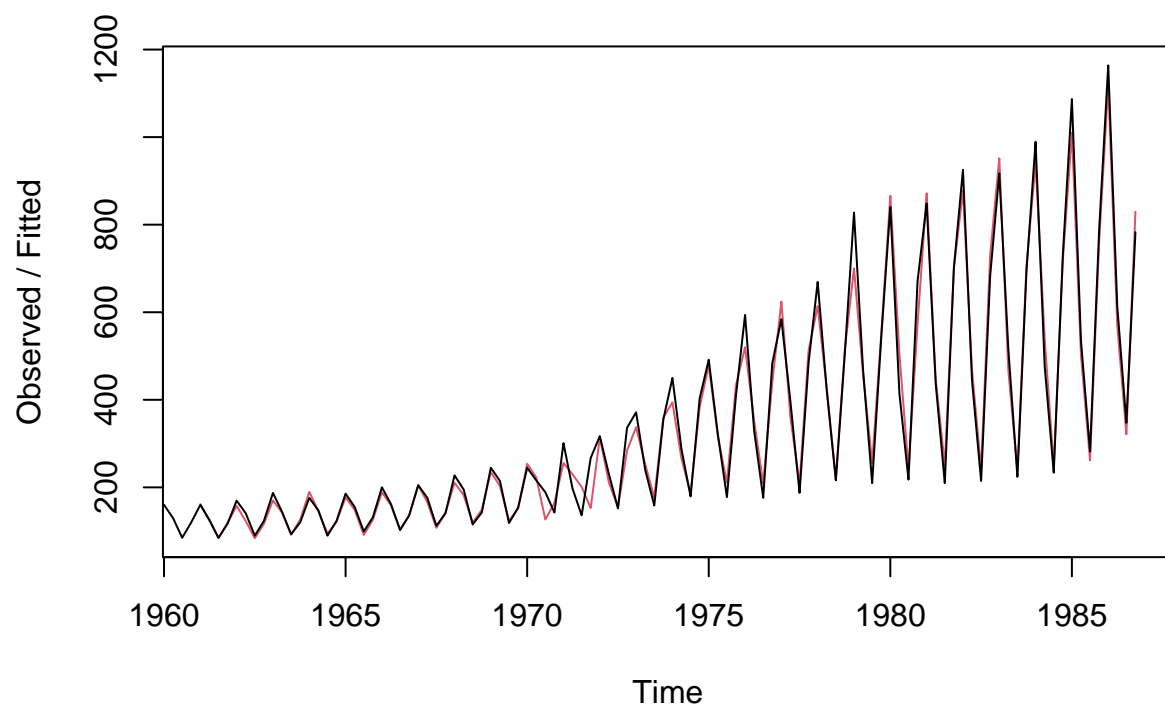
```
hist(etsUKgas$residuals)
```

**Histogram of etsUKgas\$residuals**



```
hwUKgas <- HoltWinters(UKgas)
plot(hwUKgas)
```

## Holt-Winters filtering



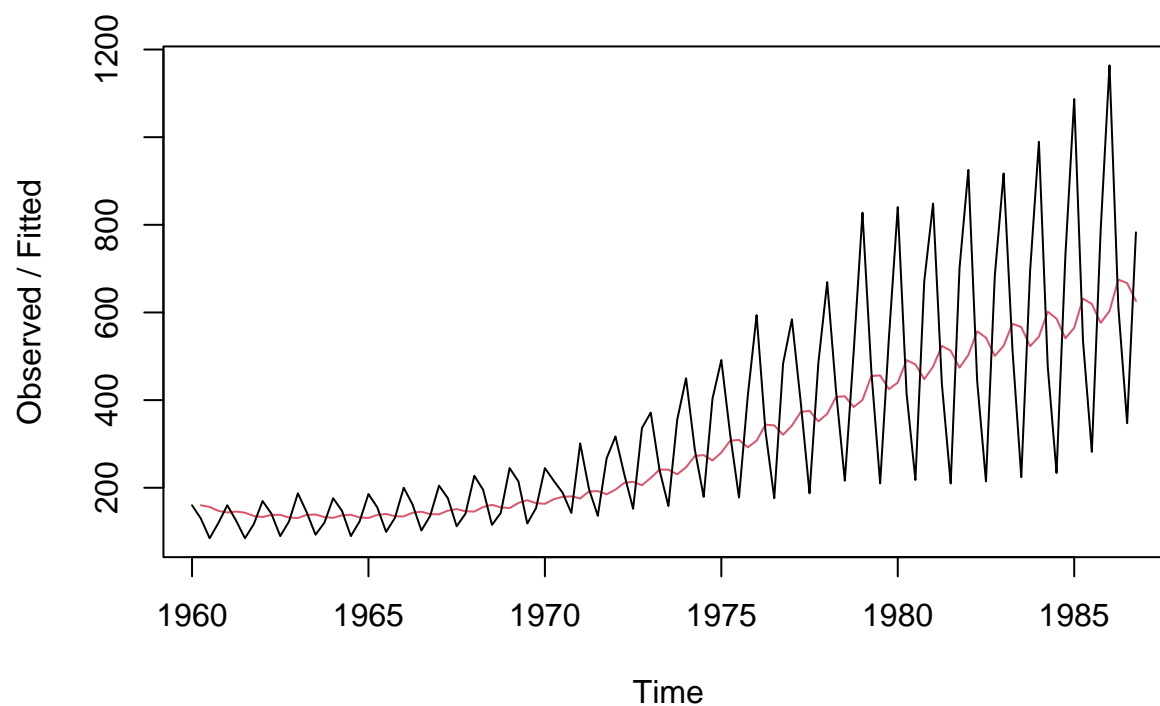
### HoltWinters

```
SSE_Simple <- HoltWinters(UKgas,beta=FALSE,gamma=FALSE)
attributes(SSE_Simple)
```

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

plot(SSE_Simple)
```

## Holt-Winters filtering



```
SSE_Simple$SSE
```

```
## [1] 3450731
```

```
head(SSE_Simple$fitted)
```

```
##           xhat    level
## 1960 Q2 160.1000 160.1000
## 1960 Q3 156.2124 156.2124
## 1960 Q4 147.0800 147.0800
## 1961 Q1 143.6298 143.6298
## 1961 Q2 145.7360 145.7360
## 1961 Q3 143.0715 143.0715
```

```
#Forecast
```

```
forecast_ets_1 <- forecast.ets(etsUKgas, h=4)
plot(forecast_ets_1)
forecast_ets_2 <- forecast(etsUKgas, h=4)
plot(forecast_ets_2)
```

Forecasts from ETS(M,A,M)

