Time Series Analysis

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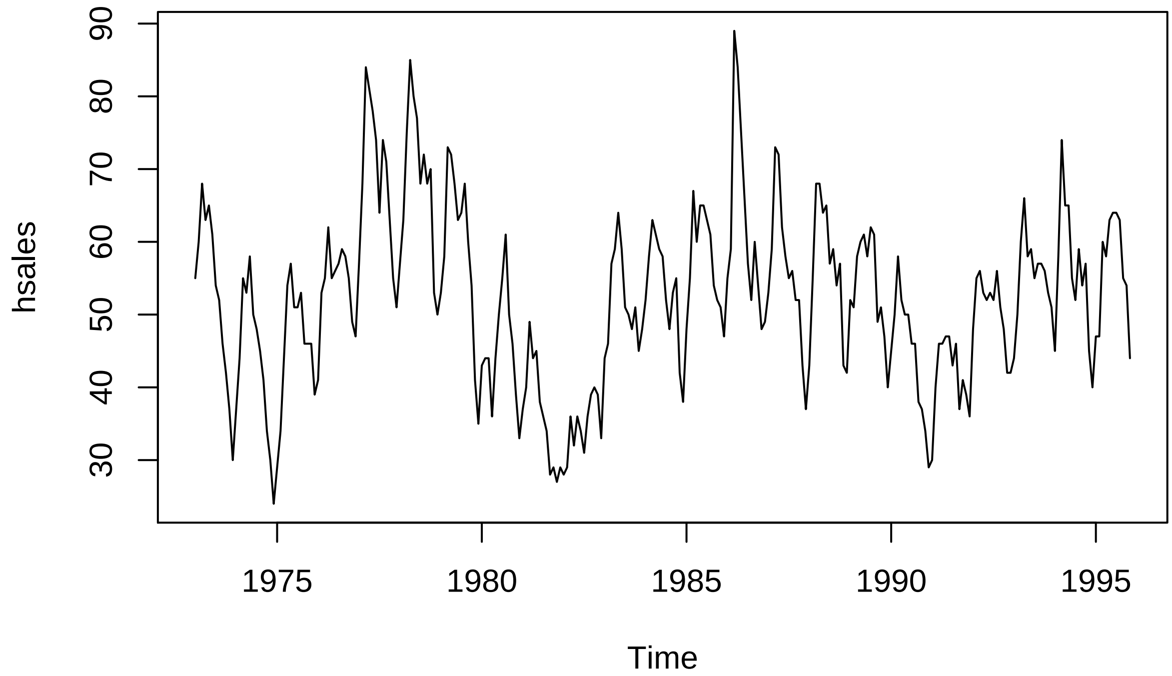
Q1. hsales data

a. Download and plot hsales data. Can you identify seosonal flactuation or trend?

```r
library(fpp) #fpp package needed to be installed
```

```
## Warning: package 'fpp' was built under R version 3.3.1

## Loading required package: forecast

## Warning: package 'forecast' was built under R version 3.3.1

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: timeDate

## This is forecast 7.1

## Loading required package: fma

## Warning: package 'fma' was built under R version 3.3.1

## Loading required package: tseries

## Warning: package 'tseries' was built under R version 3.3.1

## Loading required package: expsmooth

## Warning: package 'expsmooth' was built under R version 3.3.1

## Loading required package: lmtest
```

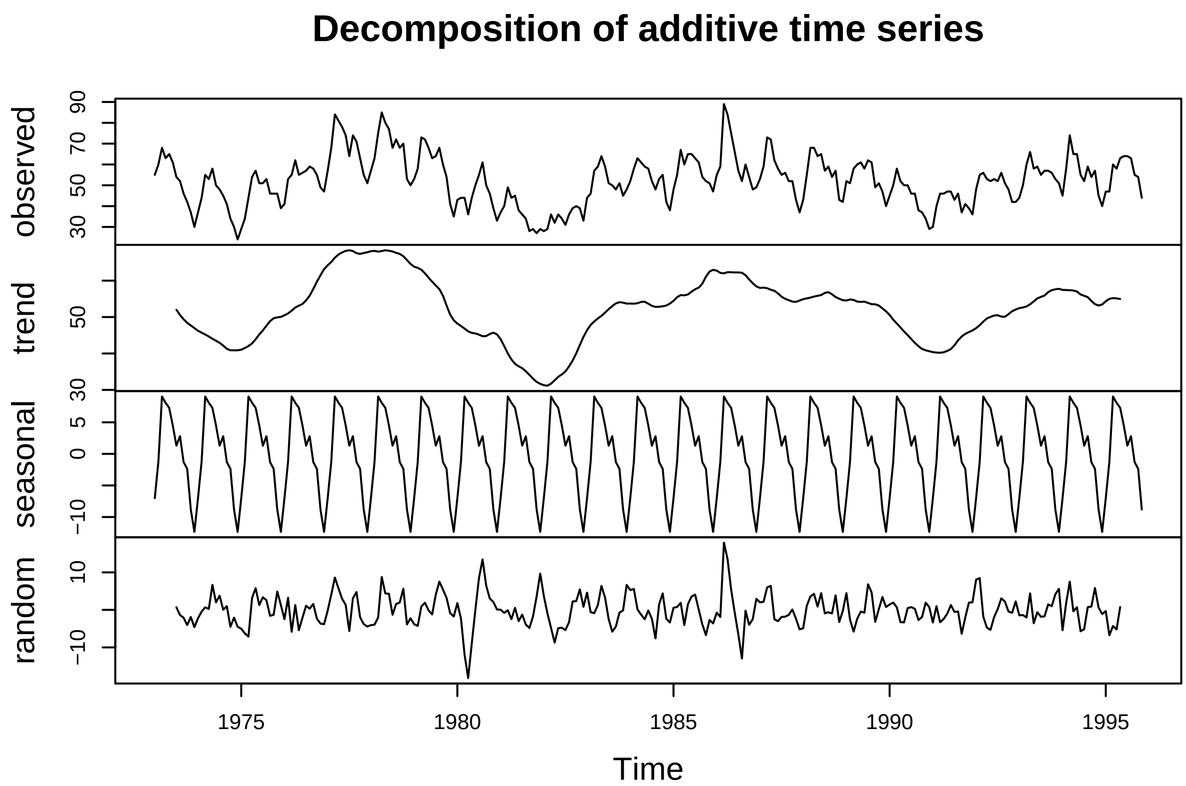
```r
data(hsales)
plot(hsales)
```



It looks like there are both seasonal and trend fluctuations

b. Use classical decomposition to calculate the trend-cycle and seosonal indices.Do the results support the graphical interpretation from part(a)?

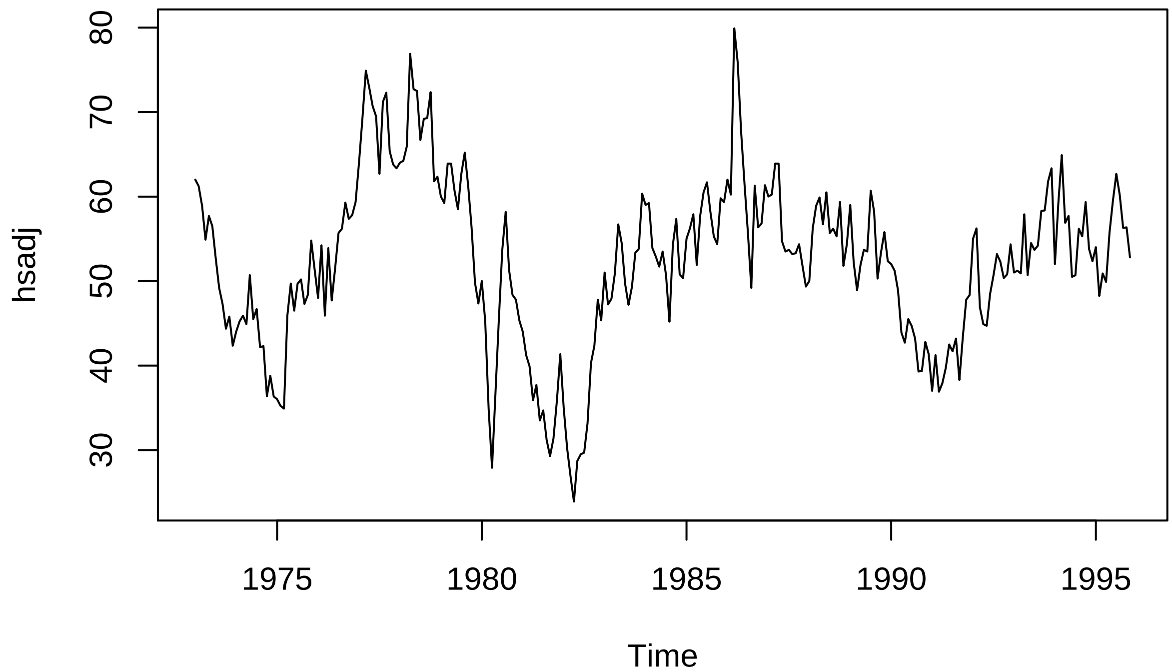
```r
fithsd <- decompose(hsales)
plot(fithsd)
```



Yes they do, the decomposition clearly shows all that fluctuations (seasonal and trend)

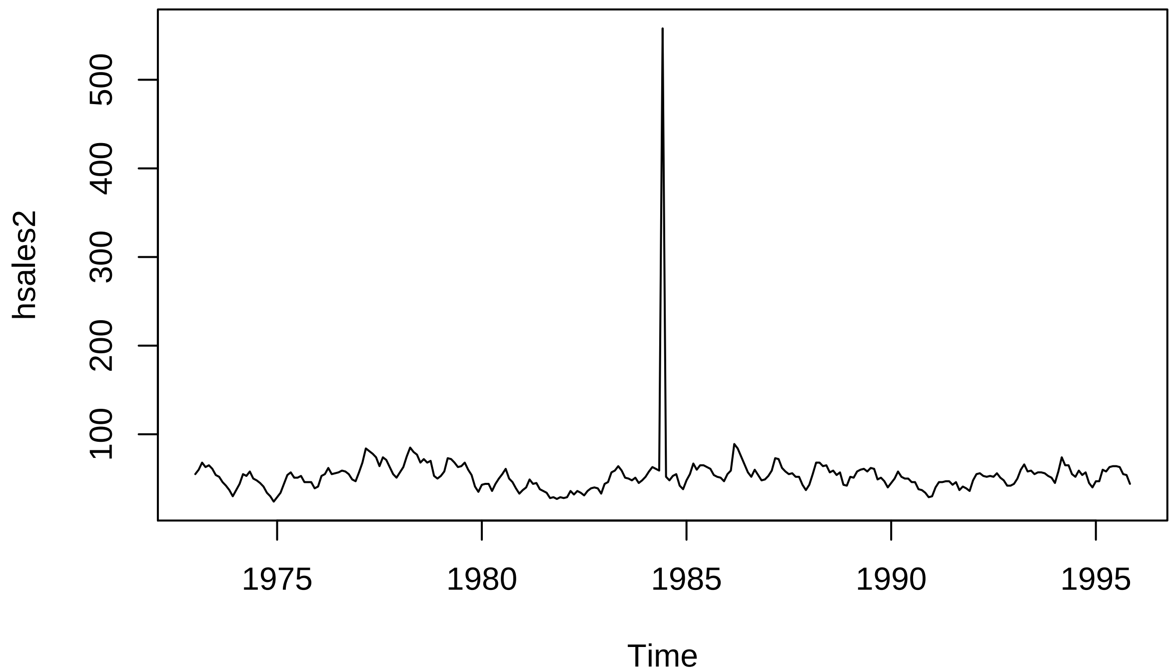
c. compute and plot the seasonally adjusted data.

```
hsadj <- seasadj(fithsd)
plot(hsadj)
```



d. change one observation to be an outlier (say 500) and recompute the the seasonally adjusted data. What is the effect of the outlier?

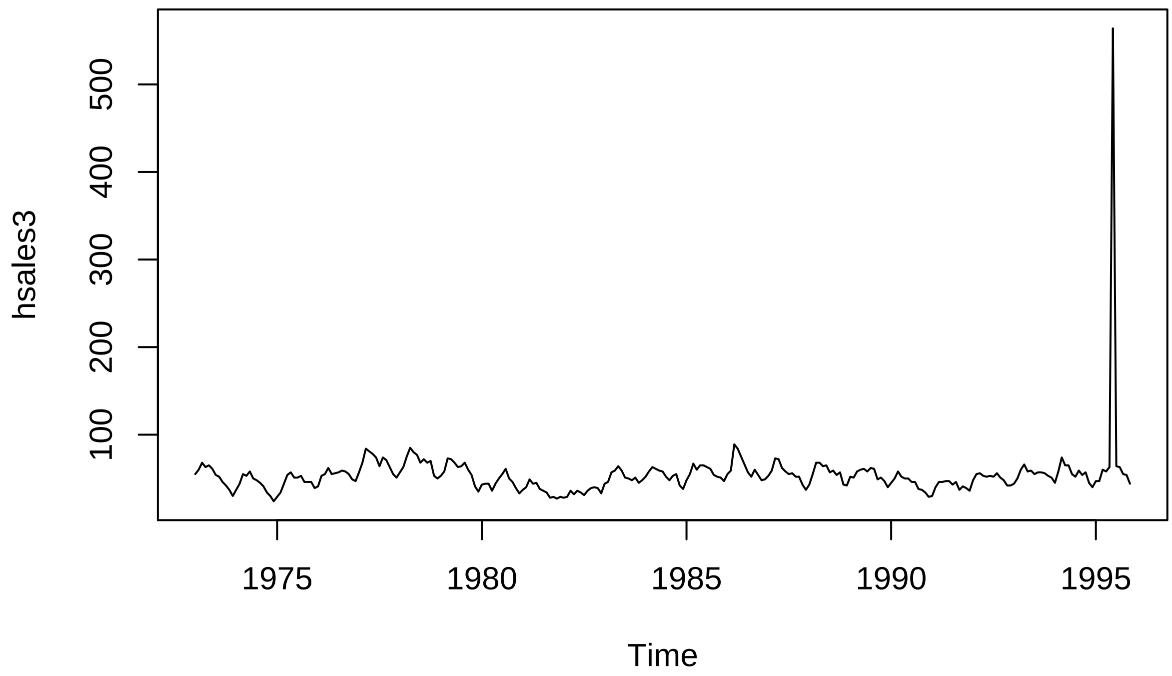
```
hsales2 <- ts(c(hsales[1:137],hsales[138]+500,hsales[139:275]),start=c(1973,1),frequency=12)
plot(hsales2)
```



The outlier causes the house sales to have a sharp change at the middle where the outlier is added at.

e. does it make any diffrence if the outlier is near end rather than in the middle of the time series?

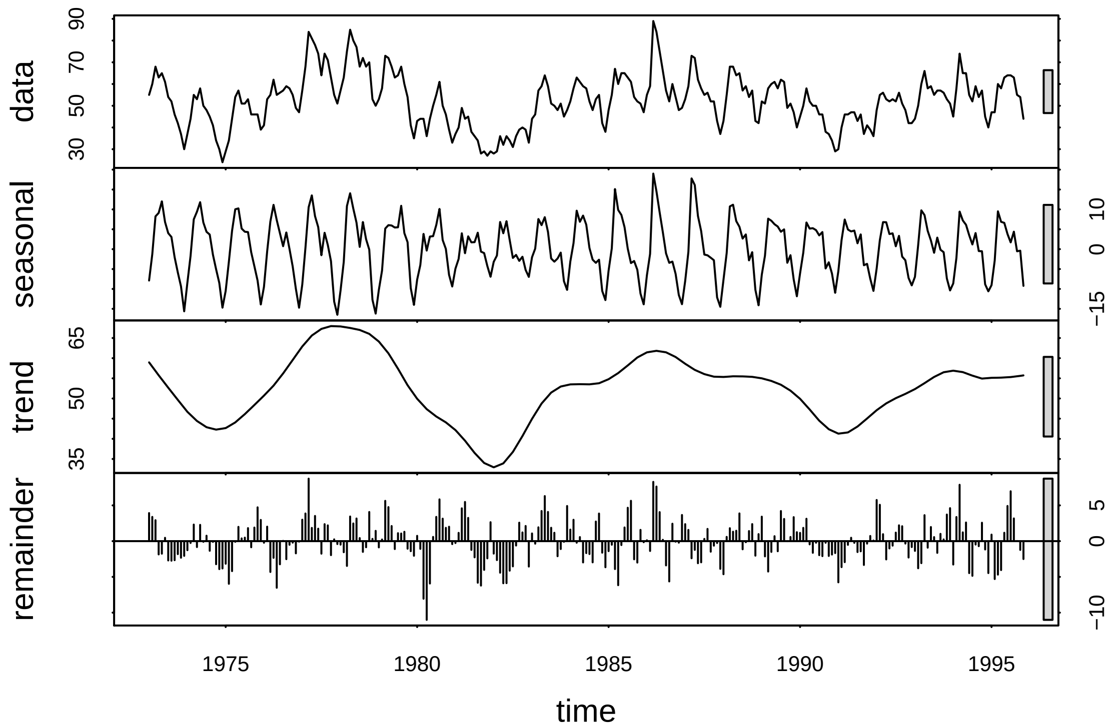
```
hsales3 <- ts(c(hsales[1:269],hsales[270]+500,hsales[271:275]),start=c(1973,1),frequency=12)
plot(hsales3)
```



Yes it does. As the outlier moves towards the end the change (sharp peak) moves with it too

f. Now use STL to decompose the series

```
fit <- stl(hsales, s.window=5)
plot(fit)
```



Q2. Volatility Analysis

a. download the data

```
library(tseries)

ADPdata <- get.hist.quote('ADP',quote="Close")
length(ADPdata)
```

```
## [1] 6438
```

b. calculate log returns

```
ADPret <- log(lag(ADPdata)) - log(ADPdata)
length(ADPret)
```

```
## [1] 6437
```

c. calculate volatility measure

```
ADPvol <- sd(ADPret) * sqrt(250) * 100
ADPvol
```

```
## [1] 34.48585
```

d. calculate volatility measure with continous lookback window

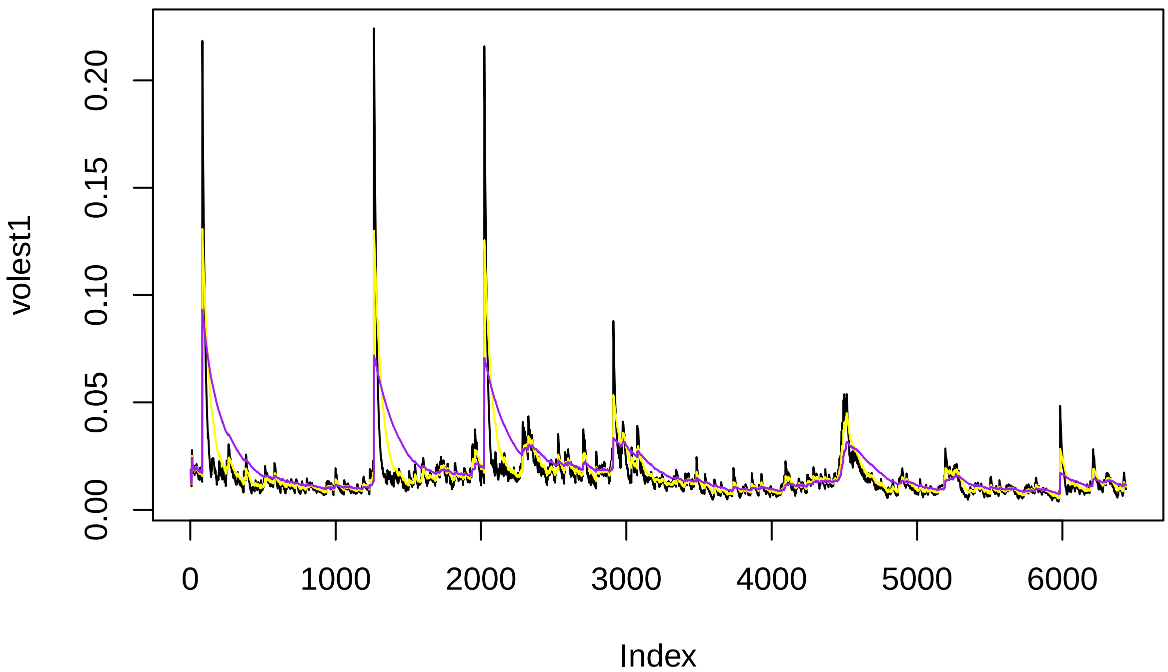
```
get
```

```
## function (x, pos = -1L, envir = as.environment(pos), mode = "any",
##     inherits = TRUE)
## .Internal(get(x, envir, mode, inherits))
## <bytecode: 0x0000000012e065b8>
## <environment: namespace:base>
```

```
Vol <- function(d, logrets)
{
var = 0
lam = 0
varlist <- c()
for (r in logrets) {
lam = lam*(1 - 1/d) + 1
    var = (1 - 1/lam)*var + (1/lam)*r^2
    varlist <- c(varlist, var)
    }
sqrt(varlist)
}
volest1 <- Vol(10,ADPret)
volest2 <- Vol(30,ADPret)
volest3 <- Vol(100,ADPret)
```

e. plot the results with a volatility curve overlay

```
plot(volest1,type="l")
lines(volest2,type="l",col="yellow")
lines(volest3, type = "l", col="purple")
```



The volatility plot shows there is a high risk for the ADP return of weight =10 at arround the beginning, between 1000 and 2000, and between 2000 and 3000 indices. Those risks are getting better and better as the weight increases to 100.