# Stat153\_hw1\_Xiaoying Liu

#### 1.

```
library(TSA)
## Warning: package 'TSA' was built under R version 3.4.4
##
## Attaching package: 'TSA'
## The following objects are masked from 'package:stats':
##
       acf, arima
## The following object is masked from 'package:utils':
##
       tar
library(forecast)
## Warning: package 'forecast' was built under R version 3.4.4
## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'zone/tz/2018e.
## 1.0/zoneinfo/America/Los_Angeles'
library(ggplot2)
## Warning: package 'ggplot2' was built under R version 3.4.4
library(gridExtra)
## Warning: package 'gridExtra' was built under R version 3.4.1
#install.packages("gtrendsR")
library(dplyr)
## Warning: package 'dplyr' was built under R version 3.4.4
##
## Attaching package: 'dplyr'
## The following object is masked from 'package:gridExtra':
##
##
       combine
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
library(gtrendsR)
## Warning: package 'gtrendsR' was built under R version 3.4.4
```

```
#microsoft=gtrends("microsoft")
#df=microsoft[[1]]
microsoft=read.csv("multiTimeline2.csv")

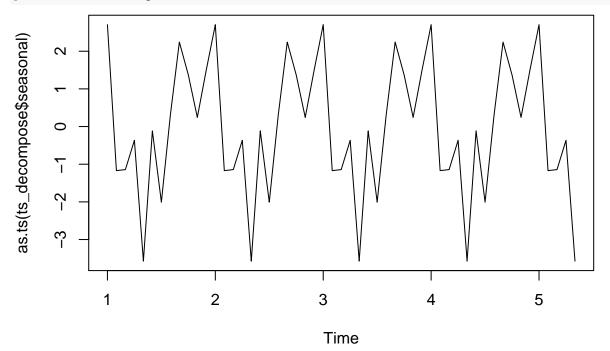
#examine data

microsoft=ts(microsoft)#global/past 5 years
t=time(microsoft)
class(microsoft)
```

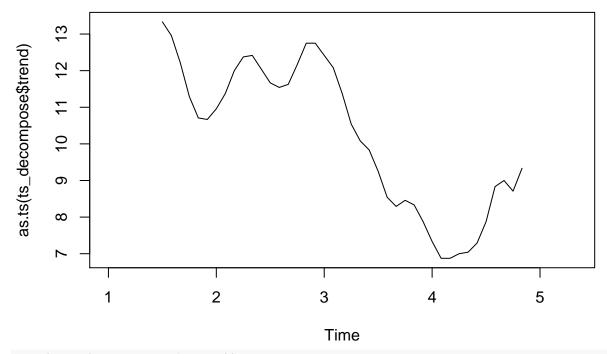
## [1] "ts"

#### play with data

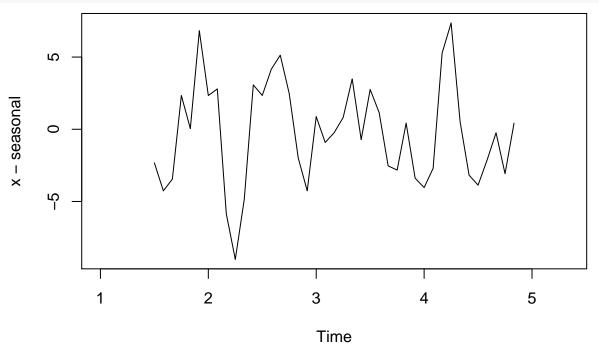
```
ts=ts(microsoft,frequency=12)
ts_decompose=decompose(ts,"additive")
plot(as.ts(ts_decompose$seasonal))
```



plot(as.ts(ts\_decompose\$trend))



#### plot(as.ts(ts\_decompose\$random))



#### ts\_decompose\$random

##	Jan	Feb	Mar	Apr	May	Jun
## 1	NA	NA	NA	NA	NA	NA
## 2	2.33709491	2.79542824	-5.85734954	-9.01012731	-4.84346065	3.07320602
## 3	0.87876157	-0.91290509	-0.23234954	0.82320602	3.48987269	-0.71846065
## 4	-4.03790509	-2.70457176	5.26765046	7.36487269	0.53153935	-3.17679398
## 5	NA	NA	NA	NA	NA	
##	Jul	Aug	Sep	Oct	Nov	Dec
## 1	-2.32609954	-4.26359954	-3.45109954	2.34056713	0.04890046	6.82320602

```
## 2 2.34056713 4.15306713 5.13223380 2.46556713 -1.99276620 -4.26012731 ## 3 2.75723380 1.15306713 -2.53443287 -2.82609954 0.42390046 -3.38512731 ## 4 -3.86776620 -2.13859954 -0.24276620 -3.07609954 0.42390046 NA ## 5
```

#### 153 hw questions:

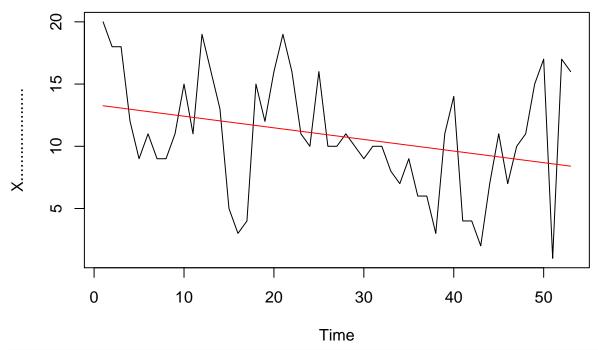
1. (a)what is time plot? Compare and discuss comments(supposed to comment on 3 graphs)

#.(b)Explain smoothing parameter? #(c) is there any trend in differenced data? #(d)isotonic trend, what does it look like?

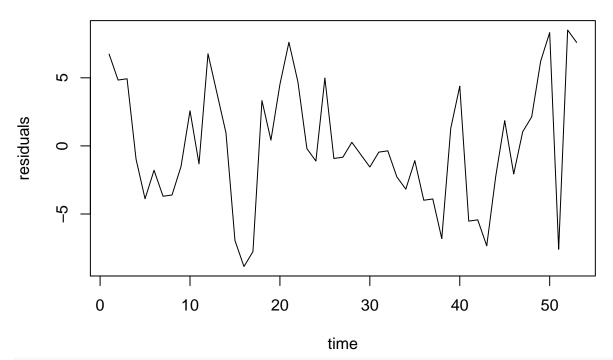
(a)fit a parametric curve to data.plot of original data and trend estimate. Time plot and correlogram of residuals. Comment on each plots

```
#try linear_fit
linear_fit <- lm(microsoft ~ t)
linear_fit

##
## Call:
## lm(formula = microsoft ~ t)
##
## Coefficients:
## (Intercept) t
## 13.35123 -0.09337
#original data plot and estimate trend
plot(microsoft)
lines(as.numeric(t), linear_fit$fitted.values, col='red')</pre>
```

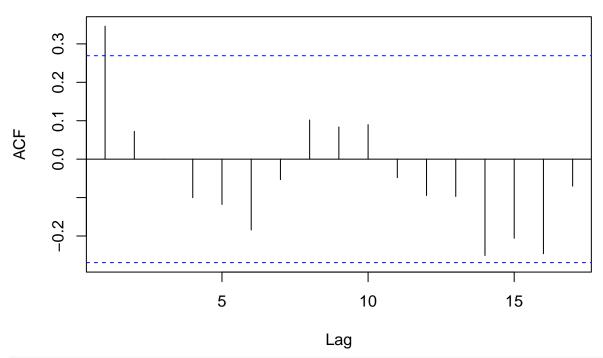


#### Residuals



#in the residual plot, we first examine if its mean is close enough to 0, mean(linear\_fit\$residuals), t  $acf(linear_fit$residuals, main='Sample ACF of the residuals')$ 

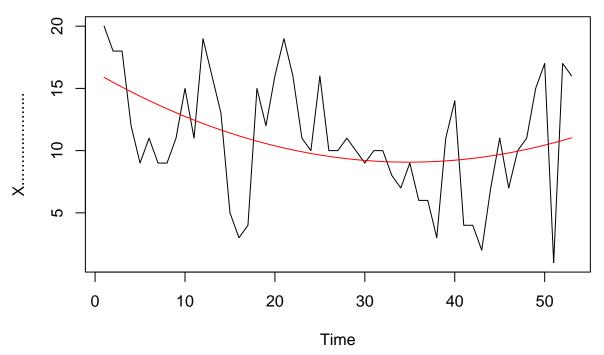
# Sample ACF of the residuals



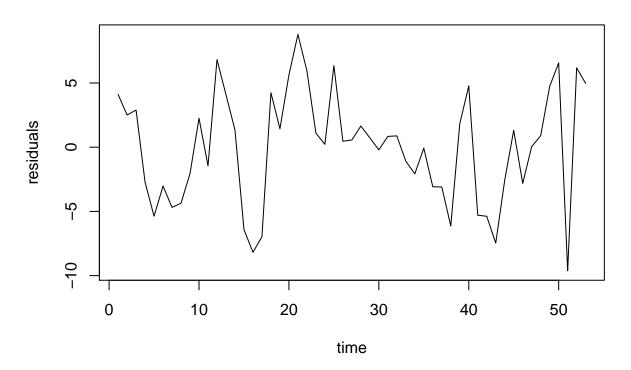
 $\textit{\#acf of residuals shows that the correlation between residuals are not significantly correlated.} (\textit{All with the correlation of the correlat$ 

```
#try quadratic fit
quadratic_fit <- lm(microsoft ~t + I(t^2))
#plot original data and estimate trend
plot(microsoft, main='microsoft')
lines(as.numeric(t), quadratic_fit$fitted.values, col='red')</pre>
```

#### microsoft

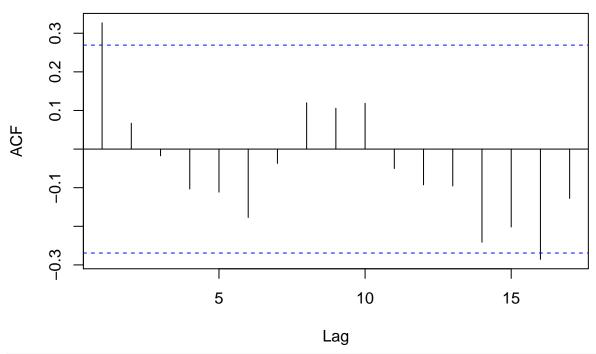


#### Residuals



#in the residual plot, we first examine if its mean is close enough to 0, mean(quadratic\_fit\$residuals)
acf(quadratic\_fit\$residuals, main='Sample ACF of the residuals')

#### Sample ACF of the residuals

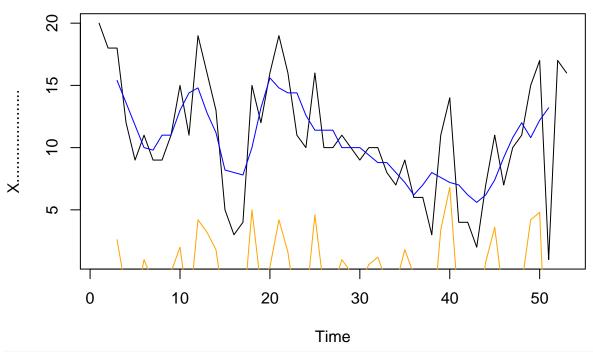


#in the residual plot, we first examine if its mean is close enough to 0, mean(linear\_fit\$residuals), t #acf of residuals shows that the correlation between residuals are not significantly correlated.(All wi

# (b)Smooth the trend. Choose smoothing parametr. 3 plots with comments.

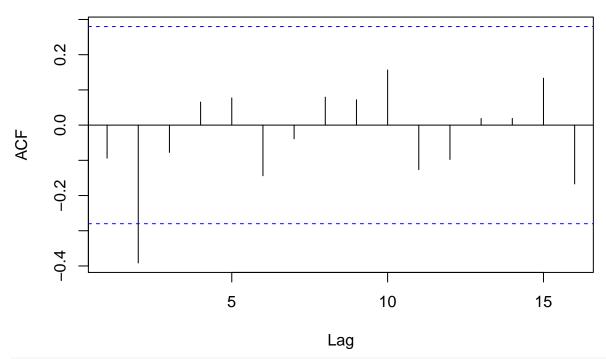
```
#smoothing to get a general idea
microsoft_smoothed <- stats::filter(microsoft, rep(1/5, 5), sides=2, method='convolution')
#I choose the
#plot original data and trend estimate
plot(microsoft, main='microsoft google trends')
lines(as.numeric(t), microsoft_smoothed, col='blue')
#there is no obvious trend after smoothing the original data. I tried several smoothing parametr, and cho
#residuals plot
residuals=microsoft_microsoft_smoothed
lines(as.numeric(t),residuals,col="orange")</pre>
```

# microsoft google trends



residuals <- residuals[!is.na(residuals)]
acf(residuals,main='Sample ACF of the residuals')</pre>

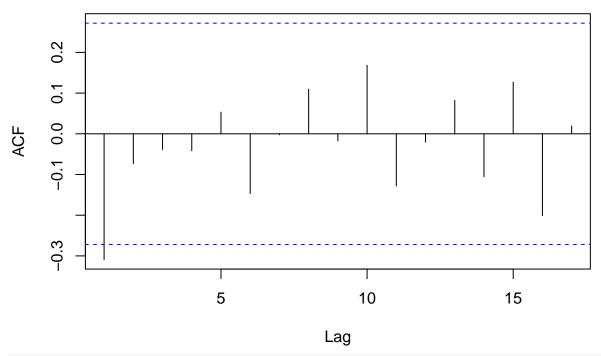
# Sample ACF of the residuals



 $\#From\ residual\ and\ acf\ plot$ , we can see there is a significant correlation for a certain lag  $h(h\ is\ bet$ 

# (c)differencing data. Is there any trend?

#### Series diff

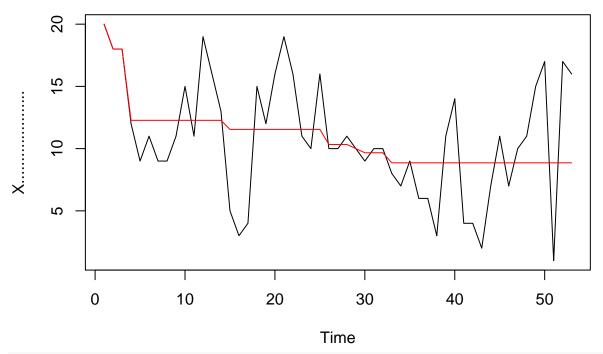


#lag=1 exceeds the blue bar significantly, this means that differding model does not capture all inform

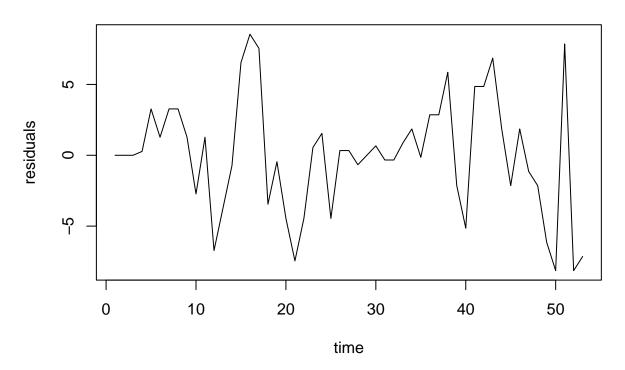
# (d)isotonic estimation. plot and comment.

```
iso_fit <- isoreg(x=t, y=-microsoft)
plot(microsoft, main='microsoft')
lines(as.numeric(t), -iso_fit$yf, col='red')</pre>
```

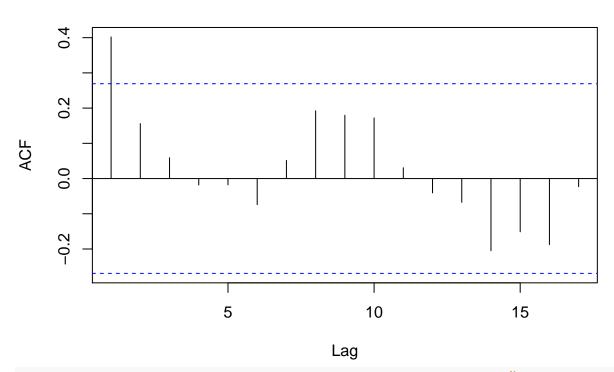
# microsoft



# Residuals



# Sample ACF of the residuals



#acf of residuals the diff shows a white-noise like pattern. We allow 5% to be outside the blue band. It