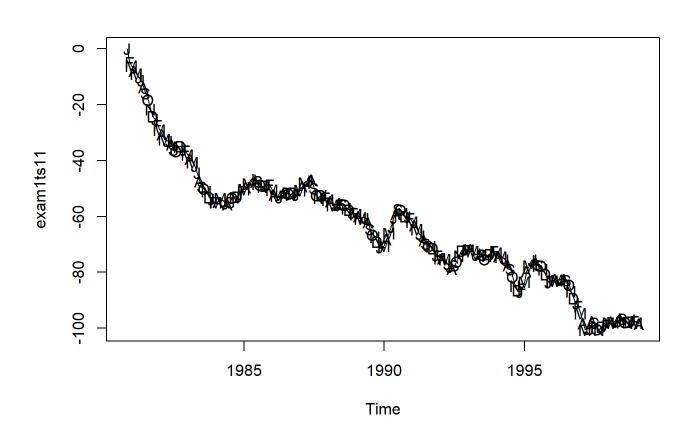
#### Exam 1 Code

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### Question 1

By looking at the code below, there seems to be a continuous negative linear trend going on. This appears to be a seasonal trend but it is not a clear pattern based on the data being on a complete fixed frequency.

```
library(TSA)
## Attaching package: 'TSA'
## The following objects are masked from 'package:stats':
      acf, arima
## The following object is masked from 'package:utils':
##
##
      tar
library(tseries)
## Registered S3 method overwritten by 'quantmod':
## method
                     from
## as.zoo.data.frame zoo
library(forecast)
## Registered S3 methods overwritten by 'forecast':
## method
                       from
    fitted.Arima
## fitted.fracdiff fracdiff
                       TSA
   plot.Arima
   residuals.fracdiff fracdiff
load(url("http://goo.gl/nGgyoh"))
months <- c("J", "F", "M", "A", "M", "J", "J", "A", "S", "O", "N", "D")
plot(exam1ts11)
points(exam1ts11, pch=months)
```



#### Question 1 B)

exam1ts11 The period for this time series is from 1981 to 1999. It does appear that this data has a more cyclic pattern going on. The cyclic variation decreases over time.

By using the Dickey-Fuller Test, we are able to conclude that this time series is indeed stationary

```
adf.test(exam1ts11, k=0)

## Warning in adf.test(exam1ts11, k = 0): p-value smaller than printed p-value

##
## Augmented Dickey-Fuller Test
##
## data: exam1ts11
## Dickey-Fuller = -4.4814, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
acf(exam1ts11)
```

# 

Series exam1ts11

The x-axis donates the time lag,

while the y-axis displays the estimated autocorrelation. Looking at this data, we can say that each observation is positively related to its recent past observations. However, the correlation decreases as the lag increases. Since it is moving to zero relatively quickly, we can conclude that this time series is stationary.

## Question 2

So here the estimated slope and intercept are B1 = -3.92862 and B0 = 7754.67728, respectively.

```
model1=lm(exam1ts11~time(exam1ts11))
summary(model1)
##
## Call:
## lm(formula = exam1ts11 ~ time(exam1ts11))
## Residuals:
      Min
                 1Q Median
                                  3Q
                                          Max
## -15.4448 -3.4544 -0.0898 3.5513 27.2704
## Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
## (Intercept) 7754.67728 173.20424 44.77 <2e-16 ***
## time(exam1ts11) -3.92862 0.08704 -45.14 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 6.832 on 218 degrees of freedom
## Multiple R-squared: 0.9033, Adjusted R-squared: 0.9029
## F-statistic: 2037 on 1 and 218 DF, p-value: < 2.2e-16
```

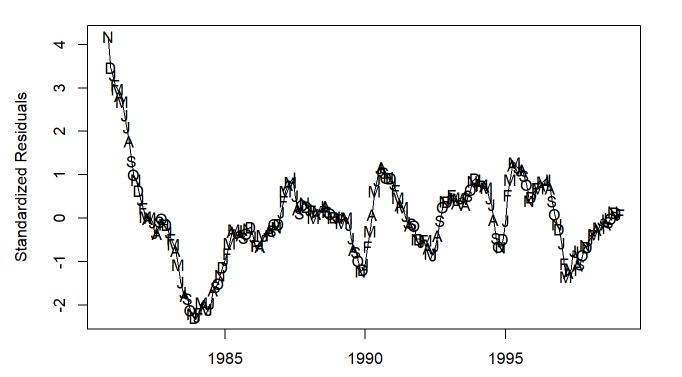
## Question 3

For both of the parameters, the p value is 2e-16. We are able to reject the null hypothesis because the p value passes the significance test for 0.10, 0.05, 0.01, and 0.001. We have a nice model for this time series. Our adjusted R squared also has a value of 0.9029.

### Question 4

This graph gives us a slightly better insight as to what is going on. It is showing that the declines are happening in various intervals. This could be business data.

```
plot(y=rstudent(model1), x=as.vector(time(exam1ts11)), xlab='Time',
    ylab='Standardized Residuals', type='l')
points(y=rstudent(model1), x=as.vector(time(exam1ts11)),
    pch=as.vector(season(exam1ts11)))
```



Note that the echo = FALSE

Time