

## Lecture 2: Overview of Financial Data and R

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Statistics 509 - Winter 2022

# Outline of topics

- Data
- More R with financial data
  - Basics
  - Loading data
  - Plotting
- Financial data sets
  - Stock prices, returns, log-returns
  - Bonds: corporate and treasury
  - Indices: price and value-weighted
- Example Statistical Analyses

# Financial data sets

- Will have a number of data sets used in class.
- Some of this will be from the WRDS (Wharton Research Data Service) – this is a wonderful resource available to U-M students and faculty.
  - There is a wide variety of carefully curated data sets.
  - These data come with 1 year delay and are for research purposes.
  - Good and online/real-time financial data is very expensive
- Yahoo Finance also has a number of indices

# Basics I

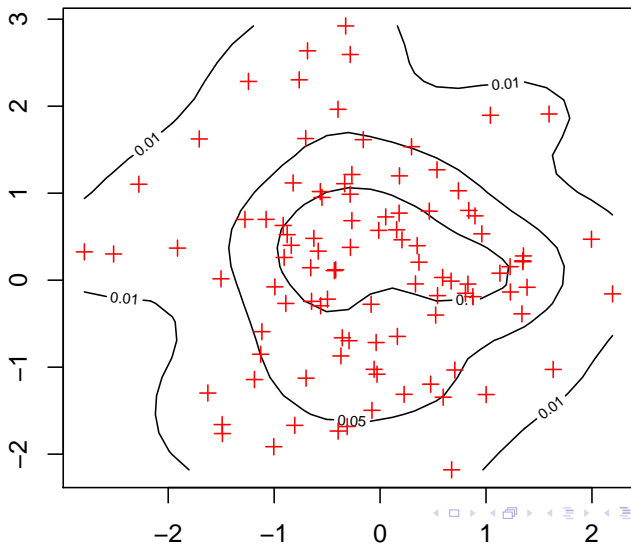
- Setting the working directory:

```
setwd("directory")
```

- Installing packages:

```
install.packages("MASS",repos="http://cran.us.r-project.org")  
library("MASS")  
set.seed(2016)  
x = matrix(rnorm(200),nrow=100,ncol=2);  
f = MASS::kde2d(x[,1],x[,2]); # or simply kde2d  
contour(f, levels = c(0.01, 0.05, 0.1) )  
points(x[,1],x[,2],col="red",pch=3)
```

## Basics II



## Loading data

Launch R or better Rstudio and load a file with daily prices of 4 stocks International Business Machines (IBM), Intel (INTC), Apple (AAPL), and Microsoft (MSFT):

```
dat = read.csv("stocks_ibm_intc_aapl_msft_1970_2015.csv", header = T)
nd = dim(dat)
names(dat)
```

```
[1] "PERMNO" "date"    "TICKER" "PRC"
```

The variable `dat` is a  $38826 \times 4$  array. Here are the last few rows

```
tail(dat)
```

	PERMNO	date	TICKER	PRC
38821	59328	12/23/2015	INTC	35.00
38822	59328	12/24/2015	INTC	34.98
38823	59328	12/28/2015	INTC	34.93
38824	59328	12/29/2015	INTC	35.44
38825	59328	12/30/2015	INTC	34.99
38826	59328	12/31/2015	INTC	34.45

# Converting the dates to Date structure and extracting stocks

```
t<-as.Date(dat$date,format="%m/%d/%Y")
stocks = list("IBM"=c(),"INTC"=c(),"MSFT"=c(),"AAPL"=c());
times = stocks;
for (tick in c("IBM","INTC","MSFT","AAPL")){
  idx0 = which(dat$TICKER==tick);
  idx1 = which(is.na(dat$PRC[idx0])==FALSE);
  times[[tick]] = t[idx0[idx1]];
  stocks[[tick]] = abs(dat$PRC[idx0[idx1]])
}
```

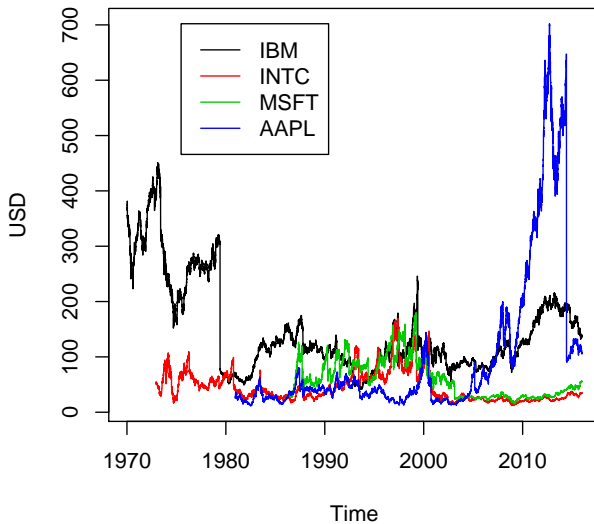
**NOTE:** Observe that we take the abs value of dat\$PRC. This is because in the CRSP data base "negative" prices indicate that this was a bid/ask average and not a closing price.

Plot the stock prices on the same graph...

```
x0 = min(times$IBM,times$INTC,times$MSFT,times$AAPL,na.rm=T)
x1 = max(times$IBM,times$INTC,times$MSFT,times$AAPL,na.rm=T)
y0 = min(stocks$IBM,stocks$INTC,stocks$MSFT,stocks$AAPL,na.rm=T)
y1 = max(stocks$IBM,stocks$INTC,stocks$MSFT,stocks$AAPL,na.rm=T)
plot(times[[1]],abs(stocks[[1]]),type="l",col=1,xlim=c(x0,x1),
      ylim=c(y0,y1),xlab="Time",ylab="USD",main="Stock Prices")
for (i in c(2:4)){
  lines(times[[i]],abs(stocks[[i]]),type="l",col=i)
}
legend(2000,y1,legend=names(stocks),lty=1,col=c(1:4))
```



## Stock Prices



## Comments on stock prices

- The huge drop in the price of IBM is due to a 4-for-1 stock split on May 31, 1979.
- From the WSJ (Wall Street Journal, Jun 9, 2015):  
*Apple has taken investors on quite a ride since it instituted a “very unusual” 7-for-1 stock split exactly one year ago today. On June 6, 2014, Apple shares closed at \$645.57 apiece. The following Monday, they opened at \$92.70 each after the stock split took effect.*
- Intel and Microsoft have had stock splits.
- Stock merges (aka reverse stock split) are also possible although less common.
- So long time series of stock prices should be treated with care.

## Returns and Log Returns

# Returns and Log Returns I

Suppose  $\{X_t\}$  is the daily/weekly/monthly (closing) stock-price of an asset.

- **Return** also known as **net return** is defined as:

$$R_t := \frac{X_t - X_{t-1}}{X_{t-1}} .$$

- Depending on the time units being days, weeks or months, we talk about daily, weekly or monthly returns, respectively.
- **Log-returns** are defined as

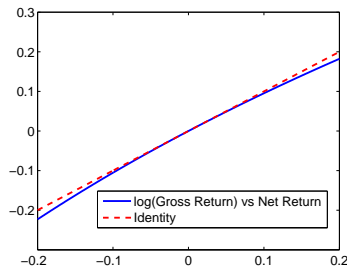
$$r_t := \ln \frac{X_t}{X_{t-1}} .$$

# Returns and Log Returns II

- By the Taylor expansion of the function  $x \mapsto \log(1 + x)$ , we have  $\log(1 + x) = x + O(x^2)$ , as  $x \rightarrow 0$ . Thus,

$$r_t =$$

## Log Return vs Net Return



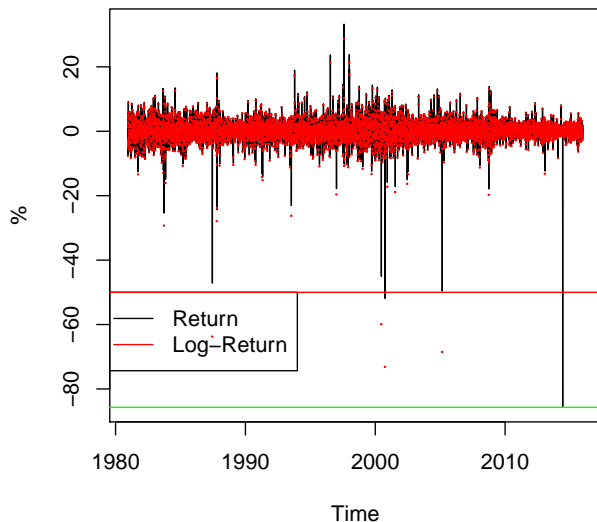
## Formulas

## Returns and Log Returns III

- **Units:** The returns have units – percent per unit time, e.g., 6% per year or 0.1% per day
  - which corresponds to

```
par(mfrow=c(1,1))
n=length(stocks$AAPL)
R.AAPL = stocks$AAPL[-1]/stocks$AAPL[-n] - 1
r.AAPL = diff(log(stocks$AAPL))
plot(times$AAPL[-1], 100*R.AAPL, type="l", xlab="Time", ylab="%", col=1)
points(times$AAPL[-1], 100*r.AAPL, col=2, cex=0.1)
legend(3050, -50, legend=c("Return", "Log-Return"), lty=1, col=c(1:2))
abline(h=-50, col="red") # 2-for-1 split
abline(h=-100*(1-1/7), col="green") # 7-for-1 split
```

# Returns and Log Returns IV



## Looking more closely at 2000 I

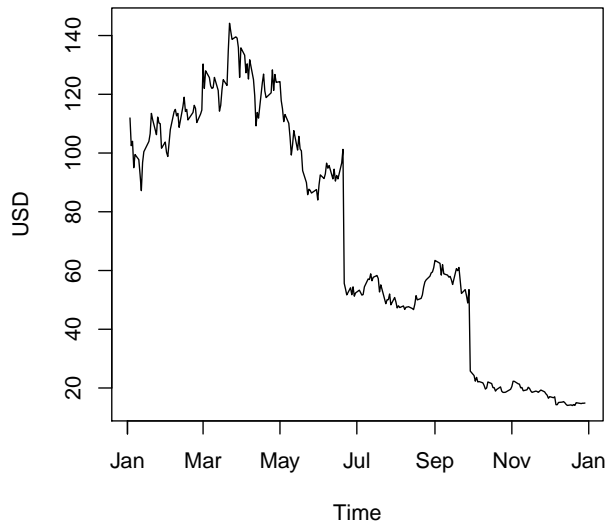
Apple's split history:	Date	Split type
	06/16/1987	2 for 1
	06/21/2000	2 for 1
	02/28/2005	2 for 1
	06/09/2014	7 for 1

```
t = as.POSIXlt(times$AAPL)
plot(t[t$year=="100"],stocks$AAPL[t$year=="100"],xlab="Time",
      ylab="USD",main="AAPL daily closing prices",type="l")
```



# Looking more closely at 2000 II

**AAPL daily closing prices**



# Apple in September 2000

- There was only one 2 for 1 split in 2000 on June 21st!
- There was a huge more than 50% drop in AAPL stock price on September 29th!
- For more details, see the CNN money article [from September 29, 2000](#).

**Caution:** The returns could be quite [heavy-tailed](#). And yes, you can lose 1/2 of your portfolio on a single day if you are not diversified!

# Multiperiod Returns

- **$k$ -period return:**

$$R_t(k) := \frac{X_t}{X_{t-k}} - 1 =$$

=

.

- **$k$ -period log return:**

$$r_t(k) := \log \left( \frac{X_t}{X_{t-k}} \right)$$

=

=

.

- Log-returns are

# Adjusting for dividends

Many stocks pay dividends several times a year. This should be reflected in the returns.

- Let  $D_t$  denote the dividend paid in period  $t$  (which could be 0).
- **Adjusted returns**

$$R_t :=$$

- **Adjusted log returns**

$$r_t :=$$

**Note:**

# Statistical Properties of the Returns

For this data turns out that

- The returns are essentially **uncorrelated**, i.e.,

$$\text{Cov}(r_t, r_{t+h}) \approx 0.$$

- The squares of the returns are significantly correlated!

$$\text{Cov}(r_t^2, r_{t+h}^2)$$

- The variability or volatility of the returns **clusters**, i.e., a period of high volatility persists for some time.
- The marginal distribution of the returns has significantly **heavier tail** than the Normal distribution.

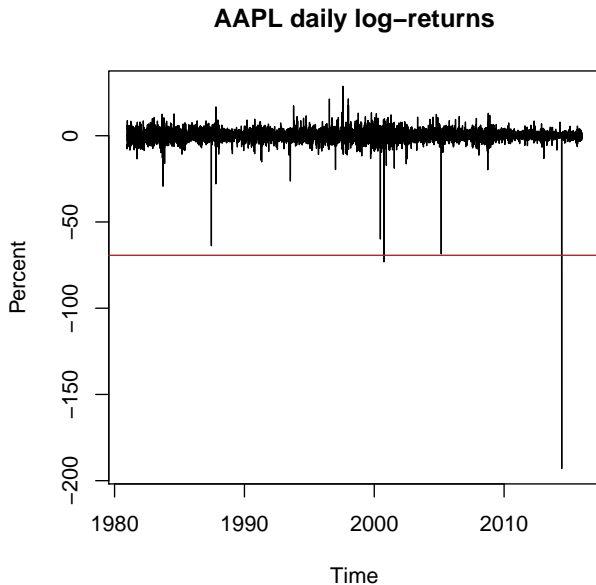
1. Above is important for applications in **Risk** and **Optimization**
2. There are limitations ....

# Raw log-returns I

We shall illustrate these facts with some basic statistical analysis of the daily log returns of AAPL.

```
r.AAPL = diff(log(stocks$AAPL))  
t.AAPL = times$AAPL[-1] # all but the first time  
plot(t.AAPL,r.AAPL*100,xlab="Time",ylab="Percent",type="l",  
      main="AAPL daily log-returns")  
abline(h=log(0.5)*100,col="red")
```

## Raw log-returns II



## Note: Concepts covered in future lectures

- A time series  $\{Y_t, t = 1, 2, \dots\}$  is **stationary**, if

$$(Y_t, t = 1, 2, \dots) \stackrel{d}{=}$$

for all  $h \in \mathbb{N}$ .

- To a first approximation and in near-term the daily returns may be modeled as stationary time series.
- Their **auto-correlation function** (ACF) is

$$\gamma_r(k) = \frac{\text{Cov}(r_t, r_{t+k})}{\sigma^2},$$

where  $\sigma^2 =$ .

- Observe the ACF plots for the time-series  $\{r_t\}$  and  $\{r_t^2\}$  with the corresponding **pointwise 95%-confidence bounds**.

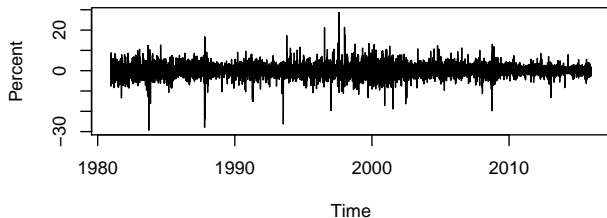


# Correlation structure II

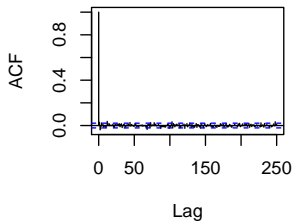
```
nf <- layout(matrix(c(1,1,2,3),2,2,byrow = TRUE), c(2,2), c(2,2), TRUE)
#layout.show(nf)
plot(t.AAPL[r.AAPL>-0.5],r.AAPL[r.AAPL>-0.5]*100,xlab="Time",ylab="Percent",typ
      main="AAPL daily log-returns: no splits and extremes")
acf(r.AAPL[r.AAPL>-0.5],#na.action = na.pass,
    main="Auto-Correlation Function",lag.max = 250)
acf(r.AAPL[r.AAPL>-0.5]^2,#na.action = na.pass,
    main="ACF: Squared log returns",lag.max = 250)
```

# Correlation structure III

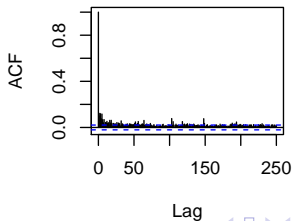
**AAPL daily log-returns: no splits and extremes**



**Auto-Correlation Function**



**ACF: Squared log returns**



# Quantile-Quantile Plots I

- Let  $Y_i$ ,  $i = 1, \dots, n$  be some data that want to model with a (cumulative) distribution  $F$ . The **quantile-quantile plot** is a good way of checking whether the model agrees with the data.
- The **generalized** quantile function of the distribution  $F$  is defined as:

$$F^{-1}(p) = \inf\{y : F(y) \geq p\}.$$

- The **QQ-plot** is a plot of the quantiles  $(F^{-1}(i/(n+1)), Y_{(i)}), i = 1, \dots, n$ , where

$$Y_{(1)} \leq Y_{(2)} \leq \dots \leq Y_{(n)}$$

are the order statistics of the data and the  $\frac{i}{n+1}$  quantiles of the empirical data.

- If the  $Y_i$ 's come from this model, then the plot will be approximately linear.

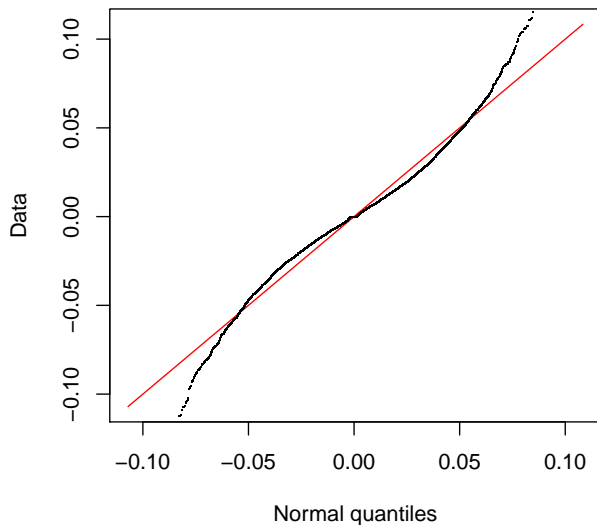
# Quantile-Quantile Plots II

- If the right-side of the plot curves **up** away from the line, then the distribution of the data has **heavier right tail** than the model.
- Similarly, if the left-side curves **down**, then the left tail of the data is heavier.
- **Important:** If the x- and y-axes are flipped, the interpretation changes. Make sure you know which axis corresponds to the data and which to the model!

```
n = length(r.AAPL[r.AAPL>-0.5])
mu  = mean(r.AAPL[r.AAPL>-0.5])
sig = sd(r.AAPL[r.AAPL>-0.5])
Normal_quantiles = qnorm(c(1:n)/(n+1),mean=mu,sd=sig)
plot(Normal_quantiles,Normal_quantiles,col="red",type="l",
     xlab="Normal quantiles",
     ylab="Data",main="Normal QQ-plot");
points(Normal_quantiles,sort(r.AAPL[r.AAPL>-0.5]),pch=".",cex=0.8)
```

# Quantile-Quantile Plots III

Normal QQ-plot



# Histograms and KDEs I

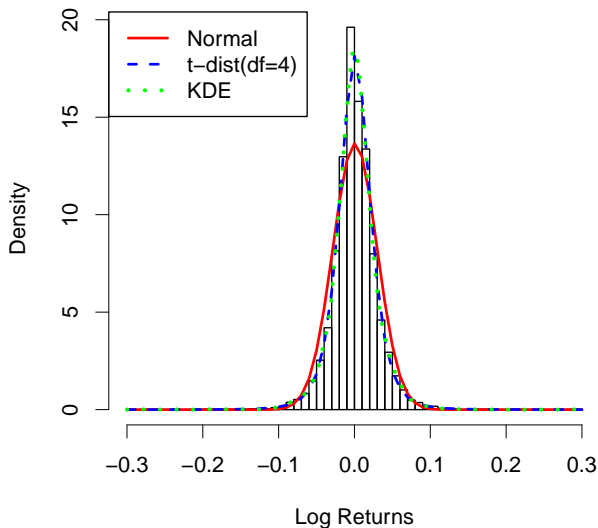
- The histogram is a standard and quick visual display of the distribution.
- The **kernel density estimators** (KDE) offer an improvement.
- Both tend to mis-represent the tails. The **transformed KDEs** provide a good alternative.
- Here is a quick plot illustrating a Normal and t-distribution fit to the AAPL log returns

# Histograms and KDEs II

```
#library("fGarch",quietly = T)
grid=seq(-0.3,0.3,0.01)
hist(r.AAPL[r.AAPL>-0.5],xlab="Log Returns",
     freq=FALSE,breaks=grid,main="AAPL Log Returns",lwd=0.5)
lines(grid,dnorm(grid,mean=mu,sd=sig),col="red",lty=1,lwd=2)
lines(grid,fGarch::dstd(grid,mean=mu,sd = sig,nu=4),
     col="blue",lty=2,lwd=2)
lines(density(r.AAPL,from=-0.3,to=0.3,n=128),
     col="green",lty=3,lwd=3)
legend("topleft",c("Normal","t-dist(df=4)","KDE"),
     col=c("red","blue","green"),lty=c(1,2,3),lwd=c(2,2,3))
```

# Histograms and KDEs III

## AAPL Log Returns



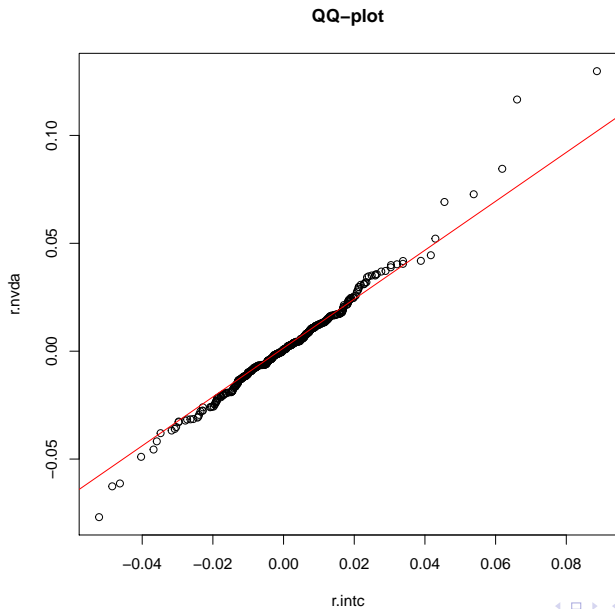


# More QQ-plots I

We explore next the goodness of fit for Student t-distribution models through QQ-plots.

```
par(mfrow=c(2,2))
for (df in c(3,4,5,6)){
  n = length(r.AAPL[r.AAPL>-0.5])
  mu = mean(r.AAPL[r.AAPL>-0.5])
  sig = sd(r.AAPL[r.AAPL>-0.5])
  t_quantiles = fGarch::qstd(c(1:n)/(n+1),mean=mu,sd=sig,nu=df)
  plot(t_quantiles,t_quantiles,type="l",col="red",
       ylab="Data",xlab="t-dist quantiles",
       main=paste("QQ-plot: t-dist(df=",df,")",sep=""))
  points(t_quantiles,sort(r.AAPL[r.AAPL>-0.5]),pch=".",cex=0.8)
}
```

## More QQ-plots II



# Stock indices

# Stock Indices I

Many single-number summaries of the financial markets exist, known as indices. They are designed to quantify the economy, various sectors (real estate, energy, manufacturing, technology, etc.) or types of stocks (e.g. large-cap, small-cap, value, etc.). Some indices just keep track of the volatility (e.g. VIX).

Here are some of the more popular indices.

- **DJIA (Dow Jones Industrial Average):** This is a simple **price average** of 30 selected stocks, multiplied by a divisor.
- The divisor is updated when there are stock-splits so as to maintain the continuity of the index.
- One drawback of DJIA and other **price average** based indices is that the price of the stock does not reflect the overall capitalization of the company.

## Stock Indices II

- **INDEXSP (S&P 500 – Standard & Poor's)** is a **capitalization-weighted average** of the 500 select stock prices. That is,

$$\text{INDEXSP} = \frac{1}{d} \sum_{i=1}^{505} N_i \times P_i,$$

where  $P_i$  is the price and  $N_i$  the number of **outstanding shares** of stock  $i$ . The divisor  $d$  is proprietary and adjusted to maintain continuity. See, e.g., the [Wikipedia](#) article.

- It is updated every 15 seconds.
- Offers a good representation of the health of the American stockmarket and economy.
- **IXIC: NASDAQ Composite** is a index composed primarily of information technology companies. It is also **capitalization-weighted average** with some restrictions on the influence of individual components.

# Stock Indices III

- **Other popular indices:** Nikkey 225 (Japan), FTSE 100 (UK), DAX (Germany), etc.

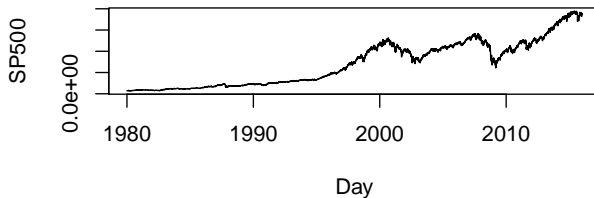
```
sp = read.csv("~/Dropbox/doc/courses/STATS_509_Fall_2016/Data/SP500_data.csv")
names(sp)

[1] "caldt"  "vwretd" "vwretx" "ewretd" "ewretx" "totval" "totcnt"
[8] "usdval" "usdcnt" "spindx" "sprtrn"

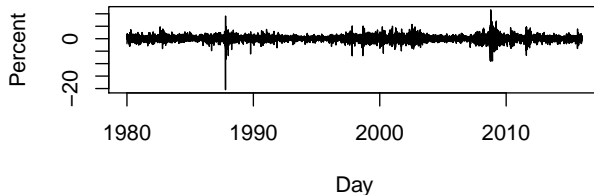
t.sp = as.Date(x=as.character(sp$caldt),format="%Y%m%d")
# Getting the times
par(mfrow=c(2,1))
plot(t.sp,sp$usdval,type="l",xlab="Day",ylab="SP500",
     ,main="Daily SP500: 1980-2015")
plot(t.sp,sp$sprtrn*100,type="l",xlab="Day",ylab="Percent",
     ,main="Daily Returns SP500: 1980-2015")
```

# Stock Indices IV

**Daily SP500: 1980–2015**



**Daily Returns SP500: 1980–2015**



# A list of a few US Stock Market crises

The large drops in the S&P 500 returns and also periods of high volatility may be associated with financial crises in the US economy.

- **Black Monday** on October 19, 1987.
- This event was followed by the [recession of the early 1990s](#).
- **Dot-com bubble** is the period of 1997–2000, which collapsed in 1999–2001. In this period many speculative Internet startups failed. Others suffered but survived. For example, the Amazon.com stock went from from \$107 to \$7 during the crash. It trades at \$1,189 per share today (January 2, 2018).
- From the Wikipedia article on the [early 2000s recession](#):

*From 2000 to 2001, the Federal Reserve, in a move to protect the economy from the overvalued stock market, made successive interest rate increases; while this may have initiated the readjustment, it is starkly contrasted with the severe, prolonged recession that would have occurred had the unsustainable growth continued unabated.*

- **Sub-prime mortgage meltdown:** Contributed to a severe US recession in the period December 2007 – June 2009.