

ARMA GARCH Processes

Abhinav Anand, IIMB

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The Autocorrelation Function (ACF)

The correlation between random variables X_1, X_2 is a measure of their linear dependence and is defined as:

$$\rho_{12} := \frac{\text{cov}(X_1, X_2)}{\sqrt{\text{var}(X_1)\text{var}(X_2)}} = \frac{\sigma_{12}}{\sigma_1\sigma_2}$$

It lies between -1 and 1 and for normal random variables $\rho_{12} = 0$ implies that the variables are independent.

If we have a sample $\{x_{1,t}, x_{2,t}\}_{t=1}^T$ the correlation can be consistently estimated by computing sample correlation:

$$\hat{\rho}_{12} = \frac{\hat{\sigma}_{12}}{\hat{\sigma}_1\hat{\sigma}_2}$$

For a time series r_t which is weakly stationary, the lag- l autocorrelation function is the correlation between r_t and r_{t-l} :

$$\rho_l = \frac{\sigma_{t,t-l}}{\sigma_t\sigma_{t-l}} = \frac{\sigma_{t,t-l}}{\sigma_t^2} = \frac{\gamma_l}{\gamma_0}$$

This follows from weak stationarity: $\sigma_t^2 = \sigma_{t-l}^2 = \gamma_0$ and $\text{cov}(r_t, r_{t-l}) = \gamma_l$.

We claim that there is no autocorrelation if $\rho_l = 0 \forall l > 0$.

To estimate the autocorrelation function of lag (say) 1, we use its sample counterpart:

$$\hat{\rho}_1 = \frac{\sum_{t=2}^T (r_t - \bar{r})(r_{t-1} - \bar{r})}{\sum_{t=1}^T (r_t - \bar{r})^2}$$

In general for lag l we consistently estimate it as:

$$\hat{\rho}_l = \frac{\sum_{t=l+1}^T (r_t - \bar{r})(r_{t-l} - \bar{r})}{\sum_{t=1}^T (r_t - \bar{r})^2}$$

The statistic $\hat{\rho}_1, \hat{\rho}_2, \dots$ is the *sample autocorrelation function* of r_t and is key to capturing the linear dependence nature of the time series in question.

Autoregressive (AR) Processes

Perhaps last period's returns may have some significant impact on the value of the returns this period. If so, its lag-1 autocorrelation may be useful for predicting the current period's value:

$$r_t = \phi_0 + \phi_1 r_{t-1} + u_t$$

where u_t is weakly stationary with mean 0 and variance σ_u^2 . This is simply equivalent to a regression where r_{t-1} is the explanatory or independent variable.

It's straightforward to check the conditional mean and variance of such a process:

$$\begin{aligned}\mathbb{E}(r_t | r_{t-1}) &= \phi_0 + \phi_1 r_{t-1} \\ \text{var}(r_t | r_{t-1}) &= \sigma_u^2\end{aligned}$$

And more generally there could be defined autoregressive processes of order p ($AR(p)$):

$$r_t = \phi_0 + \phi_1 r_{t-1} + \dots + \phi_p r_{t-p} + u_t$$

AR(1) processes

Is the AR(1) process $r_t = \phi_0 + \phi_1 r_{t-1} + u_t$ weakly stationary? This will imply that its unconditional mean and variance must be fixed in time and lag- l covariance must depend only on the lag length l .

$$\begin{aligned}\mathbb{E}(r_t) &= \phi_0 + \phi_1 \mathbb{E}(r_{t-1}) + \mathbb{E}(u_t) \\ \mathbb{E}(r_t) &= \phi_0 + \phi_1 \mu\end{aligned}$$

$$\mu = \frac{\phi_0}{1 - \phi_1}$$

This clearly implies that for the mean of an AR(1) process to exist, $\phi_1 \neq 1$ and $\phi_0 = \mu \cdot (1 - \phi_1) = \mu - \mu\phi_1$.

Hence a weakly stationary AR(1) process is:

$$\begin{aligned} r_t &= \mu - \mu\phi_1 + \phi_1 r_{t-1} + u_t \\ r_t - \mu &= (r_{t-1} - \mu)\phi_1 + u_t \\ r_t - \mu &= ((r_{t-2} - \mu)\phi_1 + u_{t-1})\phi_1 + u_t \\ &\vdots \\ r_t - \mu &= u_t + \phi_1 u_{t-1} + \phi_1^2 u_{t-2} + \dots \\ r_t &= \mu + \sum_{i=0}^{\infty} \phi_1^i \cdot u_{t-i} \end{aligned}$$

Additionally,

$$\text{var}(r_t) = \phi_1^2 \text{var}(r_{t-1}) + \sigma_u^2$$

Since for weakly stationary AR(1) processes $\text{var}(r_t) = \text{var}(r_{t-1}) = \gamma_0$ we have

$$\gamma_0 = \frac{\sigma_u^2}{1 - \phi_1^2}$$

Weak stationarity immediately implies that $\phi_1 \in (-1, 1)$.

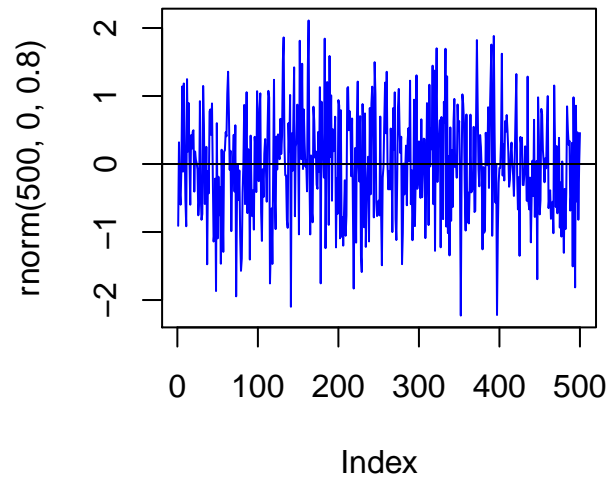
Hence taken together, for an AR(1) process to be weakly stationary it is necessary and sufficient that $\phi_1 \in (-1, 1)$;¹ and the canonical AR(1) series can be written as:

$$r_t = (1 - \phi_1)\mu + \phi_1 r_{t-1} + u_t$$

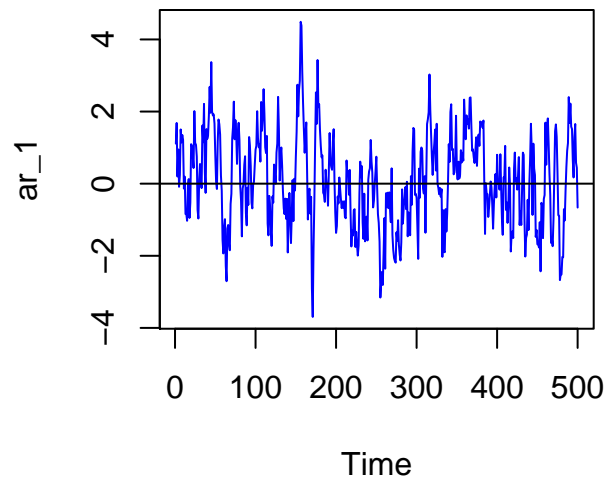
We can plot some hypothetical autoregressive processes by simulation via the function `arma.sim()` included in the `stats` package that loads by default.

¹For a general AR(p) process, the corresponding condition is: $|\phi_1| + |\phi_2| + \dots + |\phi_p| < 1$.

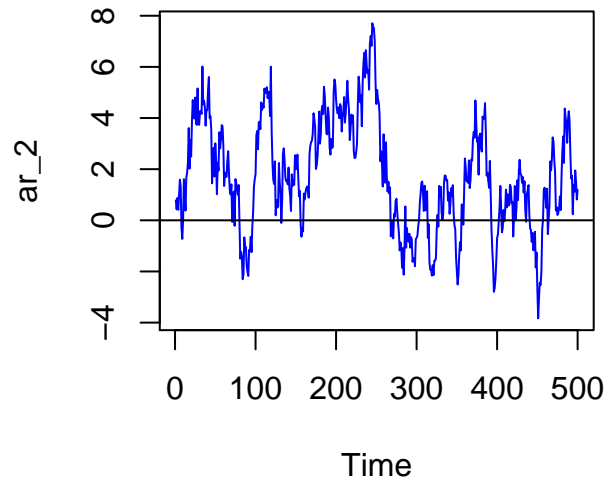
```
# AR(0)
plot(rnorm(500, 0, 0.8), type = "l", col = "blue")
abline(h = 0)
```



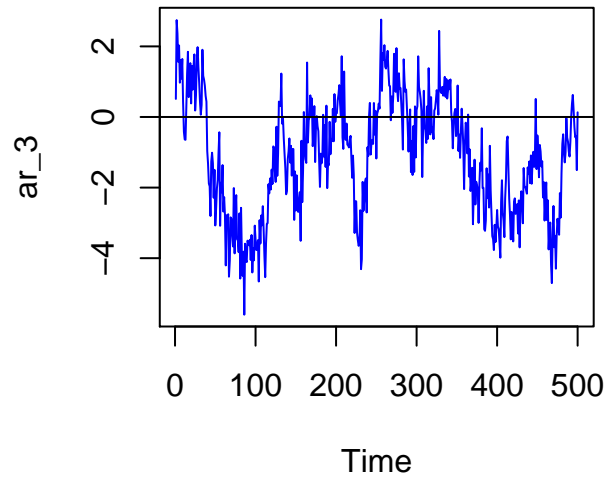
```
# AR(1)
ar_1 <- arima.sim(n = 500, list(ar = c(0.8)), sd = 0.8)
plot(ar_1, col = "blue")
abline(h = 0)
```



```
# AR(2)
ar_2 <- arima.sim(n = 500, list(ar = c(0.8, 0.15)), sd = 0.8)
plot(ar_2, col = "blue")
abline(h = 0)
```



```
# AR(3)
ar_3 <- arima.sim(n = 500, list(ar = c(0.5, 0.3, 0.15)), sd = 0.8)
plot(ar_3, col = "blue")
abline(h = 0)
```



Autocorrelation Function for AR(1) processes

We can easily check that for positive lags $l > 0$, the lagged covariance follows:

$$\gamma_l = \phi_1 \gamma_{l-1}$$

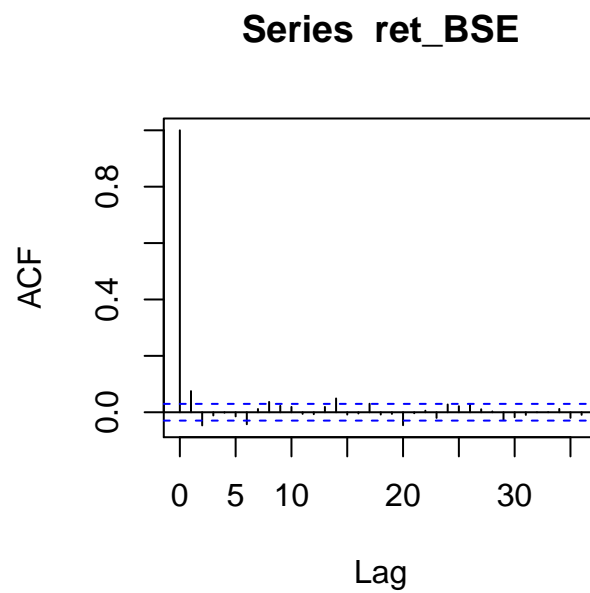
Hence it follows that for the autocorrelation function $\rho_l = \phi_1 \rho_{l-1}$; and because

$\rho_0 = 1$, $\rho_l = \phi_1^l$. This implies that the autocorrelation function of an AR(1) series decays exponentially with rate ϕ_1 and starting value 1. If $\phi_1 < 0$ the series alternates between positive and negative terms.

Illustration

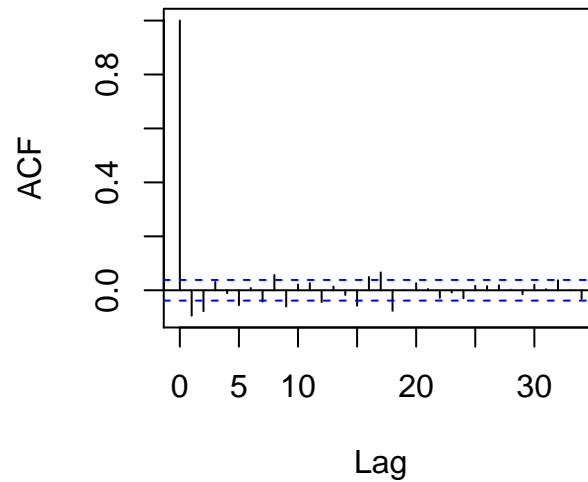
For example let's compute the sample autocorrelation function (ACF) for the financial market indices.

```
acf(ret_BSE, na.action = na.pass)
```



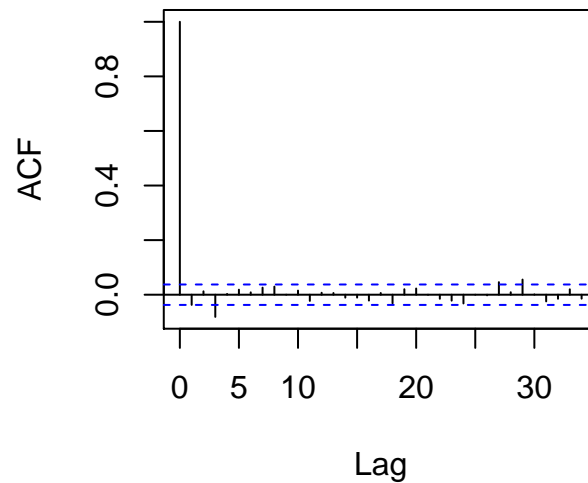
```
acf(ret_sp500, na.action = na.pass)
```

Series ret_sp500



```
acf(ret_nikkei, na.action = na.pass)
```

Series ret_nikkei

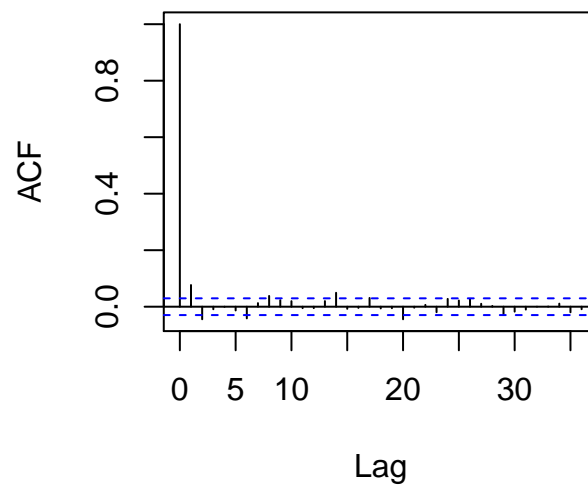


What about log-returns?

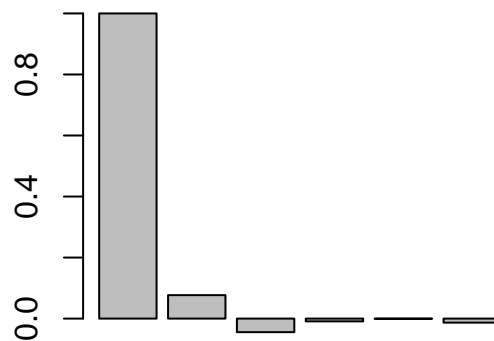
```
logret_BSE <- func_pr_to_logret(index_bse$Close)
logret_SP <- func_pr_to_logret(ind_sp500$SP500)
logret_Nikkei <- func_pr_to_logret(ind_nikkei$NIKKEI225)
```

```
ACF_BSE <- acf(logret_BSE, na.action = na.pass)
```

Series logret_BSE

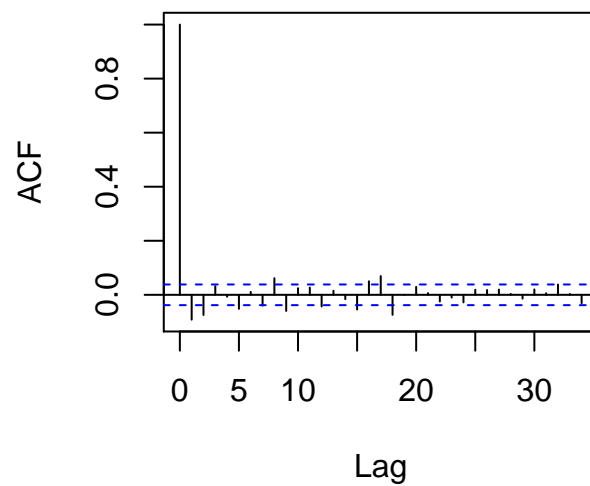


```
barplot(head(ACF_BSE$acf))
```

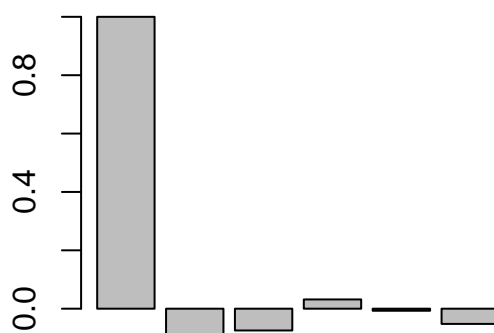


```
ACF_SP <- acf(logret_SP, na.action = na.pass)
```


Series logret_SP

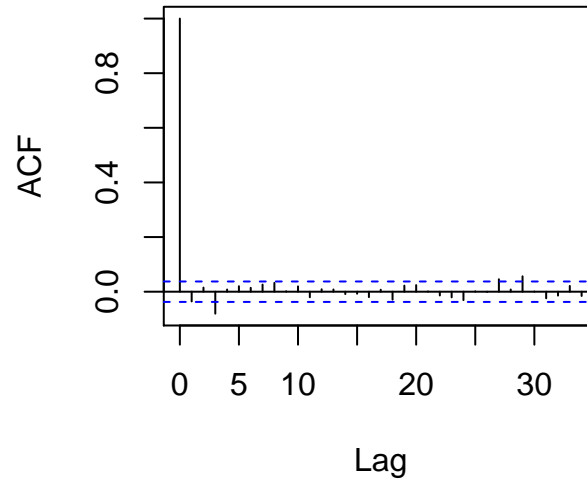


```
barplot(head(ACF_SP$acf))
```

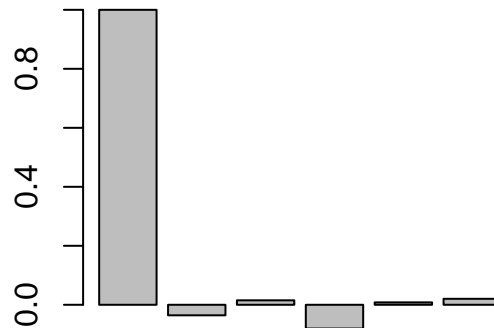


```
ACF_Nikkei <- acf(logret_Nikkei, na.action = na.pass)
```

Series logret_Nikkei



```
barplot(head(ACF_Nikkei$acf))
```



Partial Autocorrelation Functions (PACF)

Is there a way to know how many lags to include for an autoregressive return series? This issue is solved via the usage of *partial autocorrelation functions* as shown below.

Consider the following sequences of AR processes:

$$r_t = \phi_{01} + \phi_{11}r_{t-1} + u_{1t}$$

$$r_t = \phi_{02} + \phi_{12}r_{t-1} + \phi_{22}r_{t-2} + u_{2t}$$

$$r_t = \phi_{03} + \phi_{13}r_{t-1} + \phi_{23}r_{t-2} + \phi_{33}r_{t-3} + u_{3t}$$

$$r_t = \phi_{04} + \phi_{14}r_{t-1} + \phi_{24}r_{t-2} + \phi_{34}r_{t-3} + \phi_{44}r_{t-4} + u_{4t}$$

$$\vdots$$

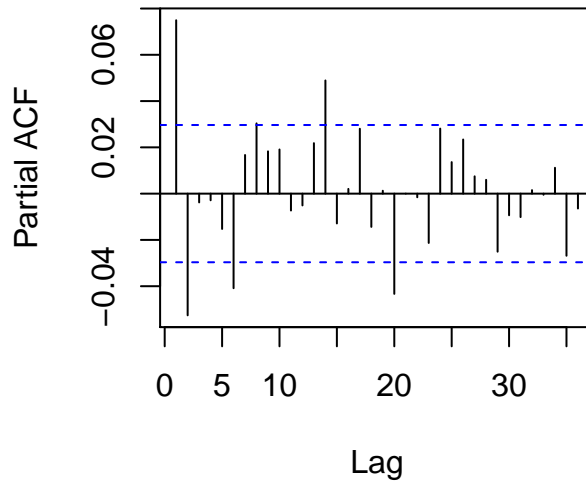
These models are merely multiple regressions and can be estimated via the standard least squares method.

In these models, $\hat{\phi}_{11}$ is called the lag 1 sample PACF of r_t , $\hat{\phi}_{22}$ of the second equation is the lag 2 sample PACF of r_t and so on. By construction, the lag 2 $\hat{\phi}_{22}$ is the marginal contribution of r_{t-2} in explaining r_t over the AR(1) model and so on. Hence if the underlying model is say AR(p) then all sample PACFs $\hat{\phi}_{11}, \dots, \hat{\phi}_{pp}$ must be different from 0 but all sample PACFs from then on: $\hat{\phi}_{p+1,p+1}, \dots = 0$. This property can be used to find the order p .

Armed with this knowledge, let's compute the PACFs for the three financial market indices:

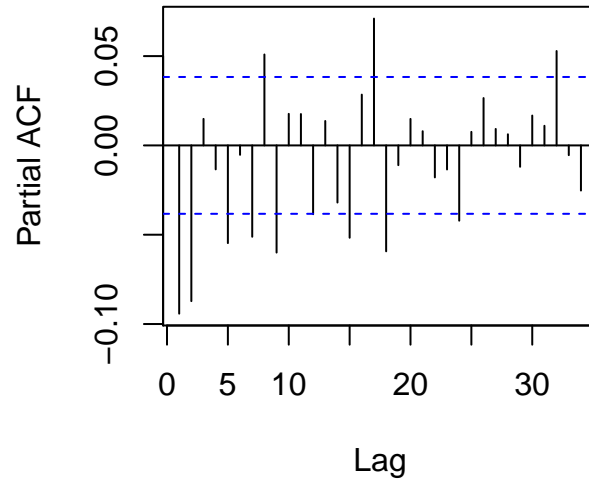
```
pacf(ret_BSE, na.action = na.pass)
```

Series ret_BSE



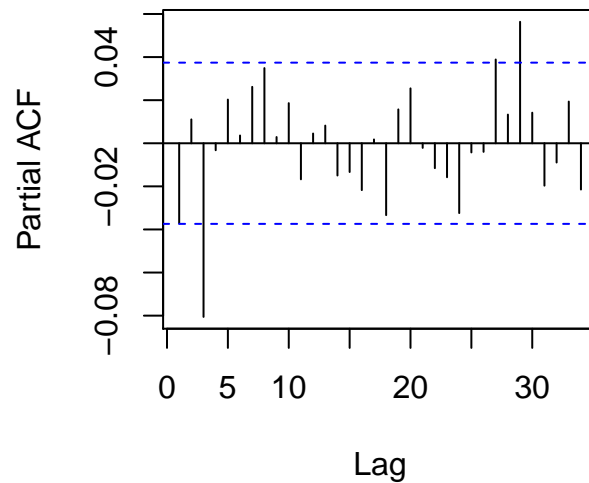
```
pacf(ret_sp500, na.action = na.pass)
```

Series ret_sp500



```
pacf(ret_nikkei, na.action = na.pass)
```

Series ret_nikkei



Information Criteria

Apart from PACF, another way to find the number of lags is the use of likelihood based information criteria. Here we look at the two most famous ones: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

$$AIC(l) = -\frac{2}{T} \cdot \ln(\text{likelihood}) + \frac{2}{T} \cdot (\# \text{parameters})$$

For a Gaussian AR(l), $AIC = \ln(\hat{\sigma}_{u,MLE}^2) + 2\frac{l}{T}$. The first term measures the goodness of fit of the model while the second penalizes the usage of parameters.

The Bayesian Information Criterion (BIC) uses a different penalty function. For a Gaussian AR(l) it takes the following form:

$$BIC(l) = \ln(\hat{\sigma}_{u,MLE}^2) + \ln(T) \cdot \frac{l}{T}$$

Moving Average (MA) Processes

Consider an infinitely long autoregressive process:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \dots + u_t$$

If this series is to be weakly stationary, the coefficients ϕ_j must decay sufficiently fast. One way to ensure this is to assume that $\phi_j = -\theta^j$ for some $\theta \in (0, 1)$.

$$r_t = \phi_0 - \theta_1 r_{t-1} - \theta_1^2 r_{t-2} - \dots + u_t$$

$$r_t + \sum_{j=1}^{\infty} \theta_1^j r_{t-j} = \phi_0 + u_t$$

The same form can be written for r_{t-2} :

$$r_{t-1} + \sum_{j=2}^{\infty} \theta_1^j r_{t-j} = \phi_0 + u_{t-1}$$

Solving for the above two equations, we get:

$$r_t = \phi_0(1 - \theta_1) + u_t - \theta_1 u_{t-1}$$

This indicates the AR model is a weighted average of shocks u_t, u_{t-1} and a constant. This is a *moving average* form of order 1 or MA(1). It's straightforward to check that unlike AR processes, MA processes are *always* stationary. (Can you see why?)

The general form for the MA(q) process is:

$$r_t = c_0 + u_t - \theta_1 u_{t-1} - \theta_2 u_{t-2} - \dots - \theta_q u_{t-q}$$

Autocorrelation Function

Consider the MA(1) model with the constant term 0:

$$r_t = u_t - \theta_1 u_{t-1}$$

$$r_{t-l} r_t = u_t r_{t-l} - \theta_1 u_{t-1} r_{t-l}$$

$$\mathbb{E}(r_{t-l} r_t) = 0 - \theta_1 \mathbb{E}(u_{t-1} r_{t-l})$$

From this we see that:

$$\gamma_1 = -\theta_1 \sigma_u^2$$

$$\gamma_{l>1} = 0$$

Also, $\text{var}(r_t) = \gamma_0 = (1 + \theta_1^2) \sigma_u^2$ and this implies that for $\rho_l = \frac{\gamma_l}{\gamma_0}$ becomes:

$$\rho_0 = 1$$

$$\rho_1 = -\frac{\theta_1}{1 + \theta_1^2}$$

$$\rho_{l>1} = 0$$

Hence for MA(1) processes, while the first lag autocorrelation is nonzero, all further lags produce zero autocorrelation. This property can be exploited to locate the order of the MA process. In general, for an MA(q) process, the ACF cuts off at lag q . Since the MA(q) process only relies on its past $q - 1$ realization, it's often called a 'finite memory' process.

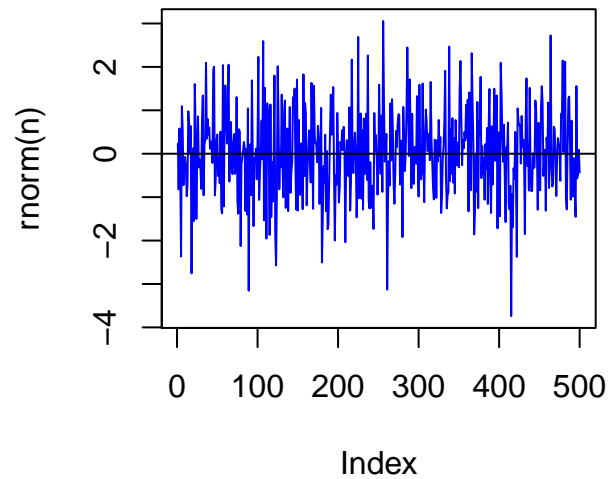
To check the order of the MA series in question, we plot the ACF of the series. If $\rho_q \neq 0$ but $\rho_{l>q} = 0$ we may conclude that the series is MA(q).

Illustrations

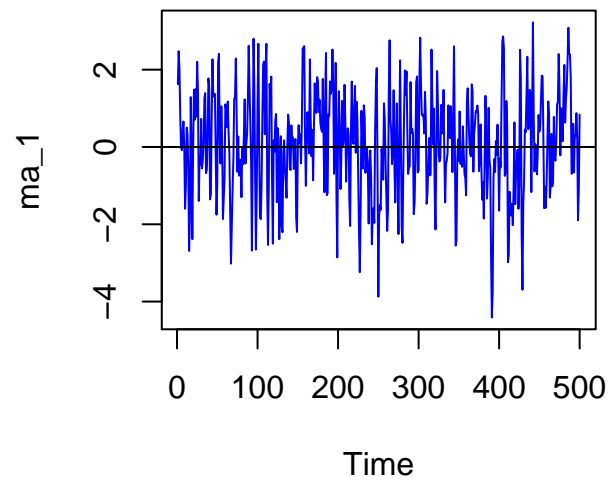
We simulate some moving average processes below:

```
n <- 500

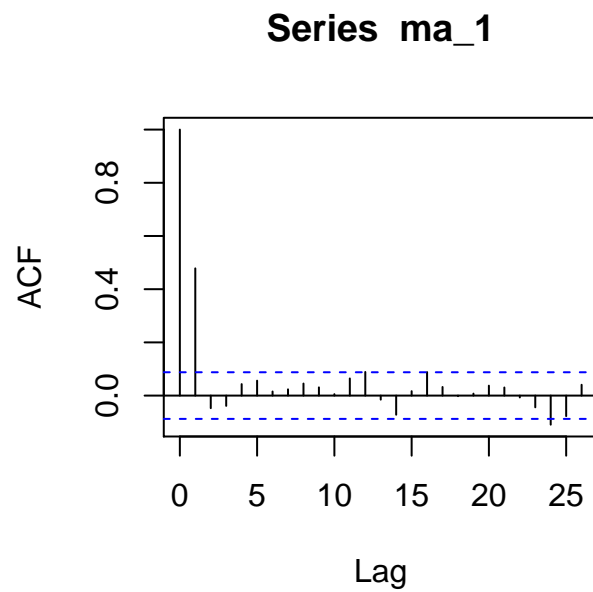
# MA(0)
plot(rnorm(n), type = "l", col = "blue")
abline(h = 0)
```



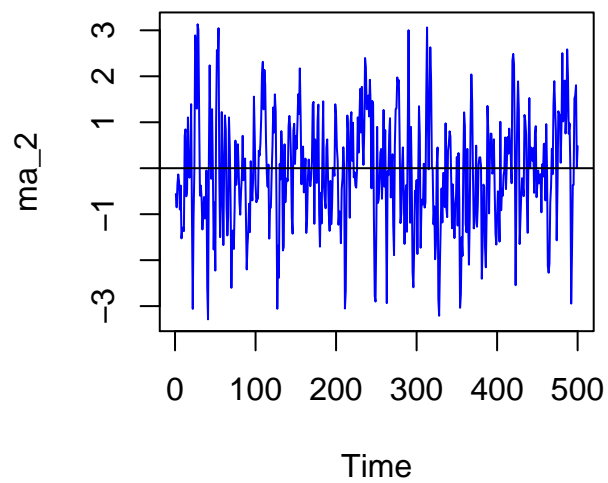
```
# MA(1)
ma_1 <- arima.sim(n = n, list(ma = c(0.8)), innov=rnorm(n))
plot(ma_1, col = "blue")
abline(h = 0)
```



```
acf(ma_1)
```

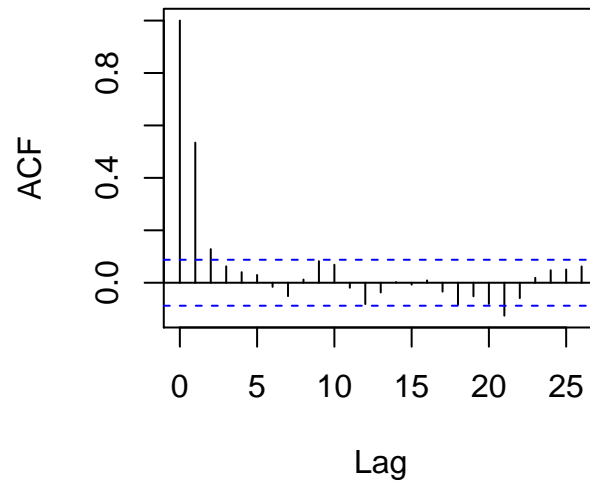


```
# MA(2)
ma_2 <- arima.sim(n = n, list(ma = c(0.8, 0.15)), innov=rnorm(n))
plot(ma_2, col = "blue")
abline(h = 0)
```

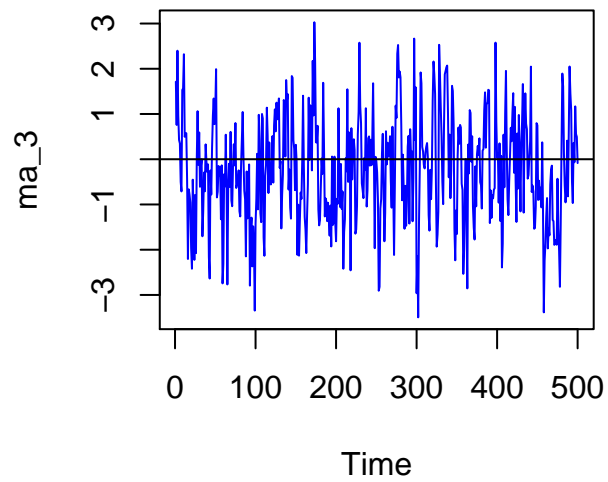


```
acf(ma_2)
```


Series ma_2

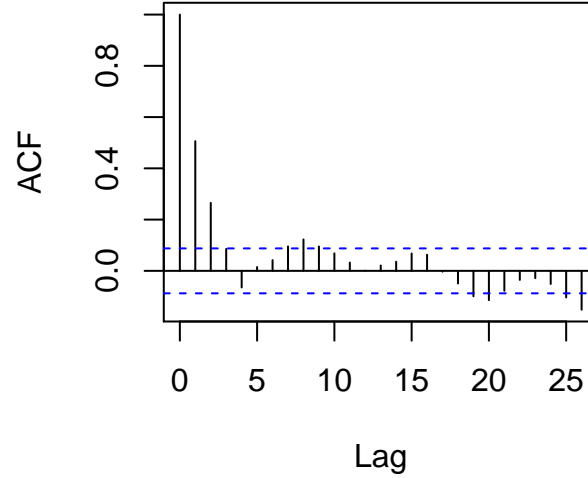


```
# MA(3)
ma_3 <- arima.sim(n = n, list(ma = c(0.5, 0.3, 0.15)), innov=rnorm(n))
plot(ma_3, col = "blue")
abline(h = 0)
```



```
acf(ma_3)
```

Series ma_3



Autoregressive Moving Average (ARMA) Processes

While in principle we could fit empirical time series to $AR(p)$ or $MA(q)$ models exclusively, often the concomitant order is very high. In order to circumvent this problem, we combine AR and MA models into a composite $ARMA(p, q)$ model with fewer parameters to estimate.

For example the $ARMA(1,1)$ series is as follows:

$$r_t - \phi_1 r_{t-1} = \phi_0 + u_t - \theta_1 u_{t-1}$$

The LHS is the AR component while the RHS is MA component.

Properties

Taking expectations we get:

$$\mathbb{E}(r_t) - \phi_1 \mathbb{E}(r_{t-1}) = \phi_0 + \mathbb{E}(u_t) - \theta_1 \mathbb{E}(u_{t-1})$$

$$\mathbb{E}(r_t) = \mu = \frac{\phi_0}{1 - \phi_1}$$

This is the same exact mean as that of an AR(1) process. Solving for the stationarity of the variance we get the same condition for the parameter $\phi_1 \in (0, 1)$ as that of the AR(1) model. It is not hard to derive the autocorrelation function of the ARMA(1,1) process which behaves the same way as that of an AR(1) process.

In general for an ARMA(p, q) process we have the following definition:

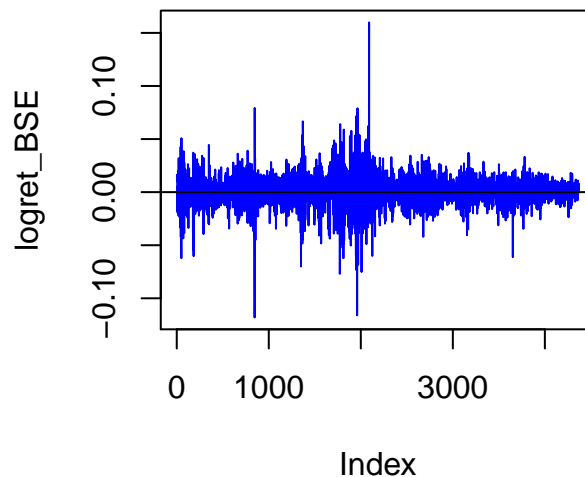
$$r_t = \phi_0 + \sum_{i=1}^p \phi_i r_{t-i} + u_t - \sum_{j=1}^q \theta_j u_{t-j}$$

Conditional Heteroskedasticity Models

In empirical time series, we do not observe volatility directly but only estimate it with the help of some other directly observed characteristics. However as discussed in Cont (2001) volatility displays some striking regularities such as volatility clustering and differential reaction to price changes.

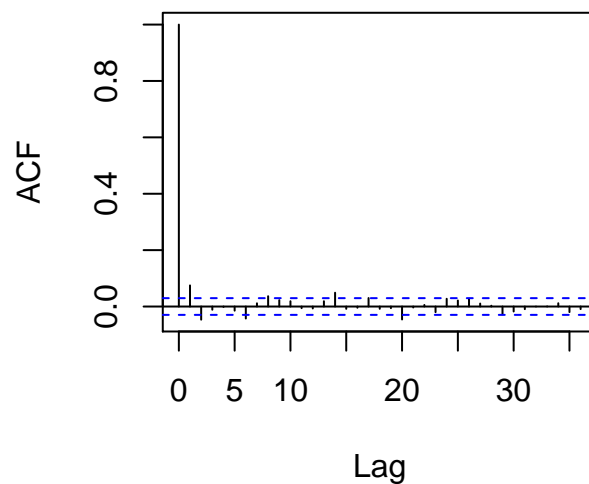
To investigate the volatility of empirical time series, we plot the daily returns and ACF of the Bombay stock exchange sensx.

```
plot(logret_BSE, type = "l", col = "blue")
abline(h = 0)
```



```
plot(acf(ret_BSE, na.action = na.pass))
```

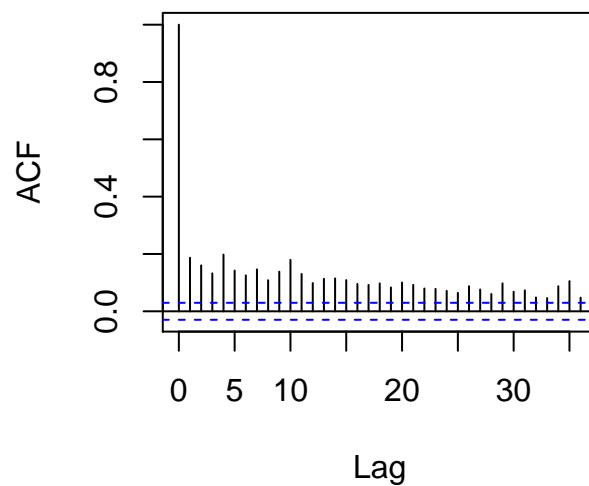
Series ret_BSE



While there seems to be no serial autocorrelation there is some dependence structure embedded in the series. We can check this for various functions of the return process such as squared returns or absolute returns:

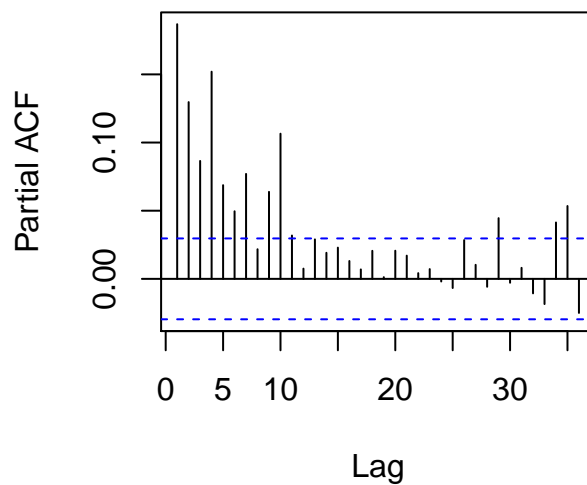
```
ret_BSE_sq <- ret_BSE^2  
acf(ret_BSE_sq, na.action = na.pass)
```

Series ret_BSE_sq



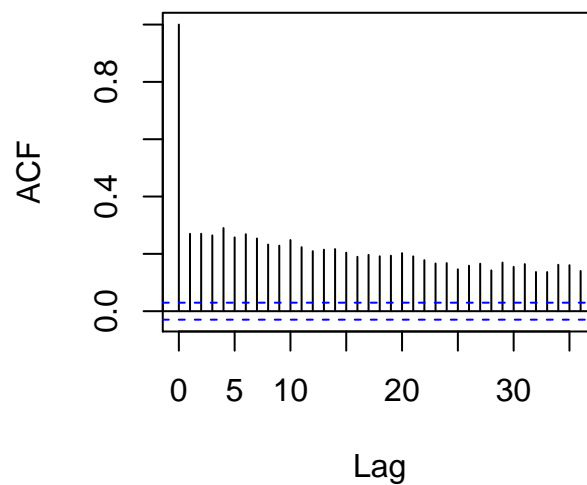
```
pacf(ret_BSE_sq, na.action = na.pass)
```

Series ret_BSE_sq



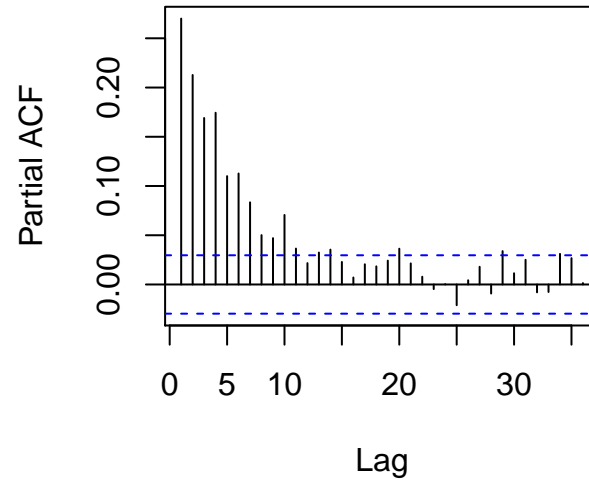
```
ret_BSE_abs <- abs(ret_BSE)  
acf(ret_BSE_abs, na.action = na.pass)
```

Series ret_BSE_abs



```
pacf(ret_BSE_abs, na.action = na.pass)
```

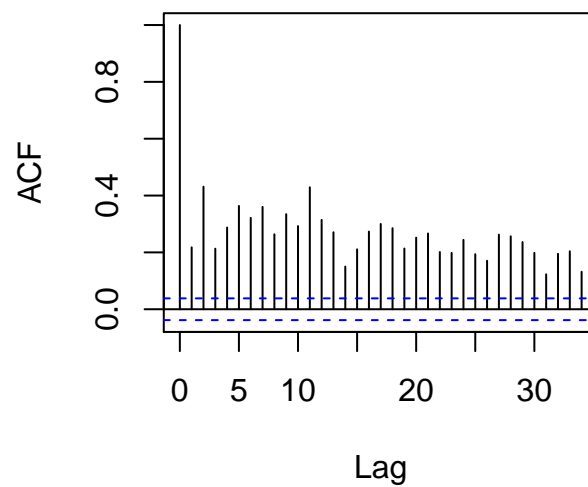
Series ret_BSE_abs



This behavior is also displayed by the other financial markets.

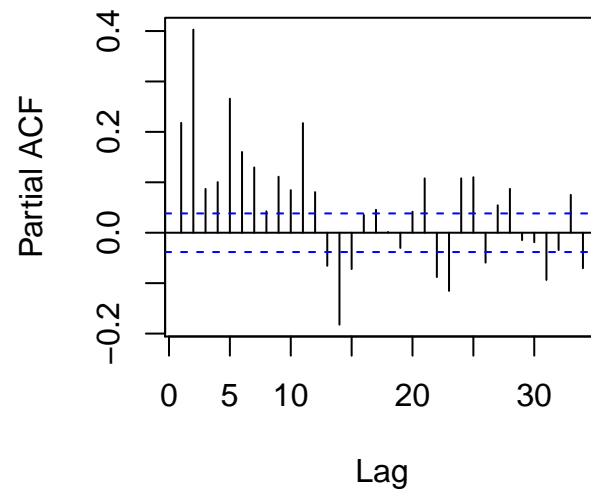
```
acf(ret_sp5002, na.action = na.pass)
```

Series ret_sp500²



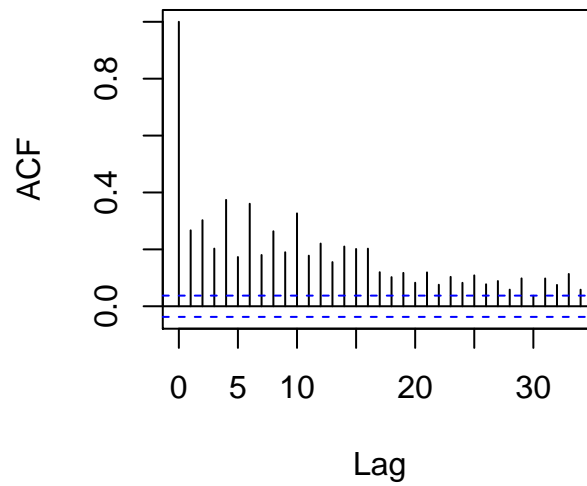
```
pacf(ret_sp5002, na.action = na.pass)
```

Series ret_sp500^2



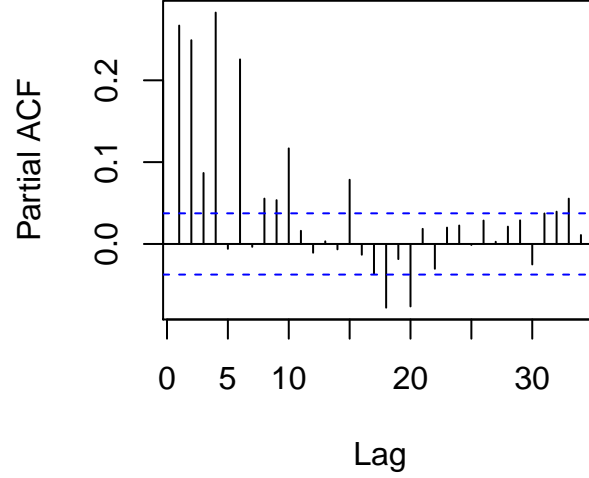
```
acf(ret_nikkei^2, na.action = na.pass)
```

Series ret_nikkei^2



```
pacf(ret_nikkei^2, na.action = na.pass)
```

Series ret_nikkei^2



The conditional mean volatility of the series may be written as:

$$\mu_t = \mathbb{E}(r_t | \mathbb{F}_{t-1})$$

$$\sigma_t^2 = \text{var}(r_t | \mathbb{F}_{t-1}) = \mathbb{E}((r_t - \mu_t)^2 | \mathbb{F}_{t-1}) = \text{var}(u_t | \mathbb{F}_{t-1})$$

Here $\mathbb{F}(\cdot)$ denotes the ‘filtration’ or the information available at the given time.

ARCH Effect

Roughly speaking if the squared residuals display autocorrelation there exist ARCH effects (autoregressive conditional heteroskedasticity effects).

Consider $r_t = \mu_t + u_t$. The square of the residual series $u_t = r_t - \mu_t$ is of interest for estimating conditional heteroskedasticity. A popular method of testing for ARCH effects is via the Ljung and Box statistics applied to the squared residuals series.

To test if autocorrelations of $\{r_t\}$ are jointly 0, the Portmanteau statistic (also called the Box-Pierce statistic) is used:

$$Q_m^* = T \cdot \sum_{l=1}^m \hat{\rho}_l^2$$

The null hypothesis is $H_0 : \rho_1 = \rho_2 = \dots = \rho_m = 0$ and the alternative is that for some i , $\rho_i \neq 0$. If $\{r_t\}_{t=1}^T$ are iid with some moment conditions, $Q^*(m) \sim \chi^2(m)$.

The *Ljung-Box* test statistic is based on the Portmanteau statistic but increases its power via the following:

$$Q(m) = T(T+2) \cdot \sum_{l=1}^m \frac{\hat{\rho}_l^2}{T-l}$$

We test for ARCH effects via the function `Box.test()` including in the `stats()` package

```
Box.test(rnorm(100)^2, type = "Ljung-Box") #Benchmark squared normals
```

```
##
## Box-Ljung test
##
## data:  rnorm(100)^2
## X-squared = 1.0548, df = 1, p-value = 0.3044
```

```
Box.test(ret_BSE_sq, type = "Box-Pierce") #Squared BSE returns
```

```
##
## Box-Pierce test
##
## data:  ret_BSE_sq
## X-squared = 152.37, df = 1, p-value < 2.2e-16
```

```
Box.test(ret_BSE_abs, type = "Ljung-Box") #Absolute BSE returns
```

```
##
## Box-Ljung test
##
## data:  ret_BSE_abs
## X-squared = 318.58, df = 1, p-value < 2.2e-16
```

The same behavior is observed for the US and Japanese market indices

```
Box.test((ret_sp500)^2, type = "Ljung-Box")

##
## Box-Ljung test
##
## data: (ret_sp500)^2
## X-squared = 115.7, df = 1, p-value < 2.2e-16

Box.test((ret_nikkei)^2, type = "Ljung-Box")

##
## Box-Ljung test
##
## data: (ret_nikkei)^2
## X-squared = 174.83, df = 1, p-value < 2.2e-16
```

Hence we may safely conclude that the market indices in question display ARCH effects—i.e., their squared residuals display autocorrelation.

Autoregressive Conditional Heteroskedasticity (ARCH)

The essential idea behind ARCH models is that while the ‘shock’ or ‘innovation’ u_t is not autocorrelated, its squared lagged terms do display autocorrelation. In other words, the ARCH(m) process assumes:

$$u_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \dots + \beta_m u_{t-m}^2$$

Here ϵ_t is iid with mean 0 and variance 1; and all β_j are non negative, with $\beta_0 > 0$. In practice it is common to assume that the shocks ϵ_t are from a standard normal, standard T or some other suitable distribution. By construction, in ARCH models, large shocks tend to be followed by other large shocks.

Properties of ARCH(1) Processes

Consider the ARCH(1) model:

$$u_t = \sigma_t \epsilon_t$$
$$\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2$$

Clearly the unconditional mean is $\mathbb{E}(\mathbb{E}(u_t | \mathbb{F}_{t-1})) = 0$ and the variance is $\text{var}(u_t) = \mathbb{E}(\mathbb{E}(u_t^2 | \mathbb{F}_{t-1})) = \beta_0 + \beta_1 \mathbb{E}(u_{t-1}^2)$ and hence

$$\text{var}(u_t) = \frac{\beta_0}{1 - \beta_1}$$

In the same way if we compute higher moments and more specifically, the kurtosis we find that the excess kurtosis of u_t is positive or in other words, for an ARCH(1) process the shocks are more fat-tailed—more likely to produce extreme values. This is consistent with empirical observations.

Order Determination of ARCH(m) Processes

The ARCH(m) process is:

$$\sigma_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + \dots + \beta_m u_{t-m}^2$$

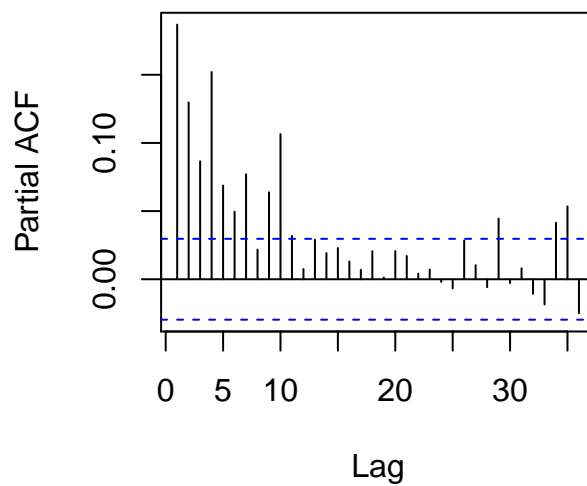
Since u_t^2 is an unbiased estimator of σ_t^2 we can interpret the ARCH(m) process as a special form of an AR(m) process for square errors.

If ARCH effects are deemed significant, we can employ the PACFs of squared residuals to find the order of the ARCH series just as we did for AR processes.

Hence we apply this idea to the market indices below.

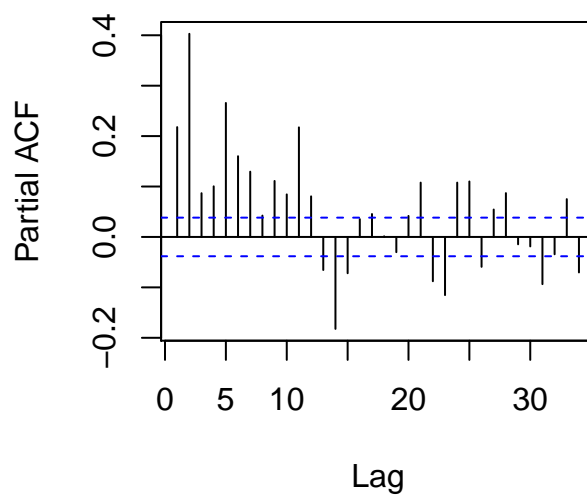
```
pacf(ret_BSE_sq, na.action = na.pass)
```

Series ret_BSE_sq



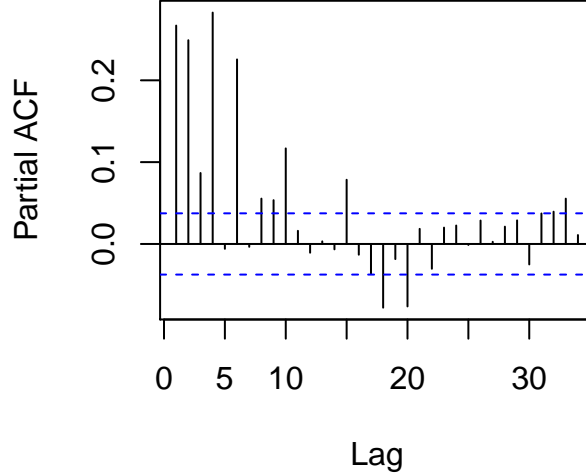
```
pacf((ret_sp500)^2, na.action = na.pass)
```

Series (ret_sp500)^2



```
pacf((ret_nikkei)^2, na.action = na.pass)
```

Series (ret_nikkei)^2



Depending on the distributional assumptions for ϵ_t we use different forms of the maximum likelihood estimation for estimating ARCH processes. Additionally to check if the ARCH model is well specified, we notice that $\tilde{u}_t = \frac{u_t}{\sigma_t}$ is an iid sequence.

Generalized ARCH (GARCH) Processes

Usage of GARCH models can shorten the order of the corresponding ARCH models. A GARCH(m, n) process is:

$$u_t = \sigma_t \epsilon_t$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^m \alpha_i u_{t-i}^2 + \sum_{j=1}^n \beta_j \sigma_{t-j}^2$$

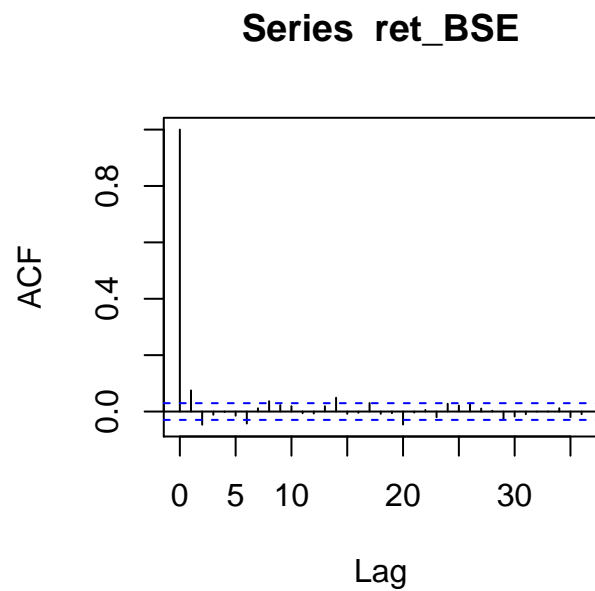
GARCH series can be thought to be ARMA series for the squared error u_t^2 . GARCH models are consistent with the phenomenon of volatility clustering and their tail distribution is fatter than that of normals.

Application: Fitting ARMA GARCH Models

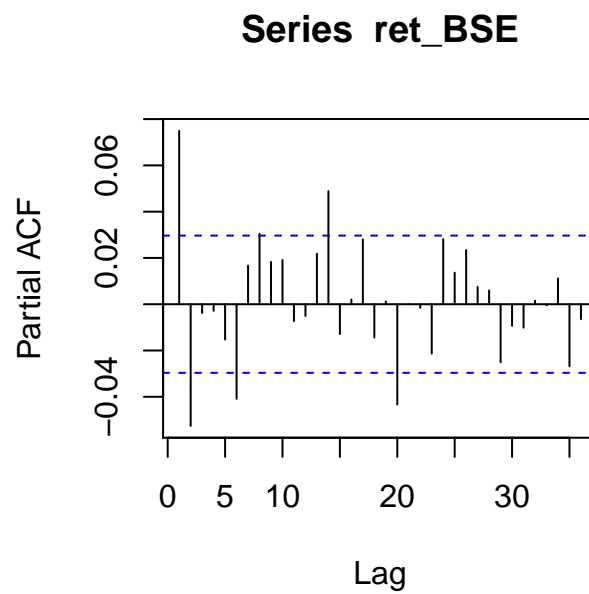
We check if the three financial market indices can be fitted satisfactorily to ARMA GARCH processes.

Sensex: Bombay Stock Exchange

```
# For lag order of AR and MA  
acf(ret_BSE, na.action = na.pass)
```



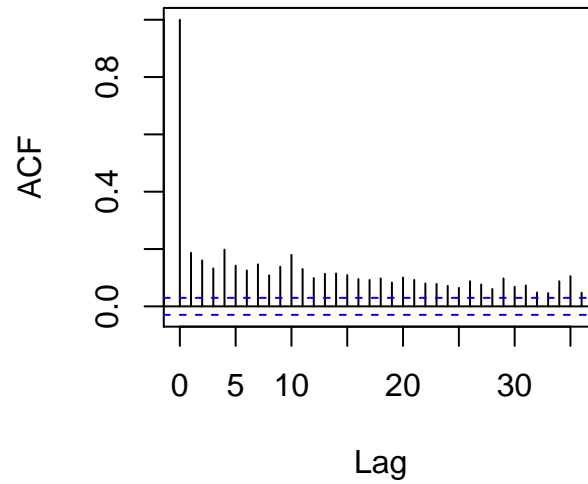
```
pacf(ret_BSE, na.action = na.pass)
```



```
# For lag order of ARCH and GARCH
```

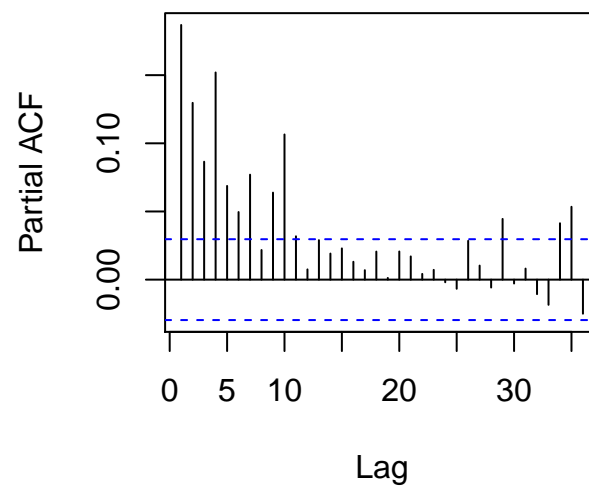
```
acf(ret_BSE_sq, na.action = na.pass)
```

Series ret_BSE_sq



```
pacf(ret_BSE_sq, na.action = na.pass)
```

Series ret_BSE_sq



References

Cont, Rama. 2001. “Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues.” *Quantitative Finance* 1 (2): 223–36.

Jondeau, Eric, Ser-Huang Poon, and Michael Rockinger. 2007. *Financial Modeling Under Non-Gaussian Distributions*. Springer Finance.

Tsay, Ruey S. 2010. *Analysis of Financial Time Series*. Third Edition. John Wiley; Sons.