

simulation_exercise.R

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```
# Simulation Exercise : 1

set.seed(10000)
mu<-3
phi1<-0.3
phi2<-0.6
zeta=1
alpha1=0.8
y=c()
y[2]=y[1]=0
v=rnorm(1000,mean=0,sd=1)
sigma_squared=c()
sigma_squared[1]=0.1

# generating the time series
for (t in 2:(length(v)-2)){
  sigma_squared[t]= zeta + alpha1*(sigma_squared[t-1]*v[t-1]*v[t-1])
  sigma_squared=append(sigma_squared,sigma_squared[t])
}

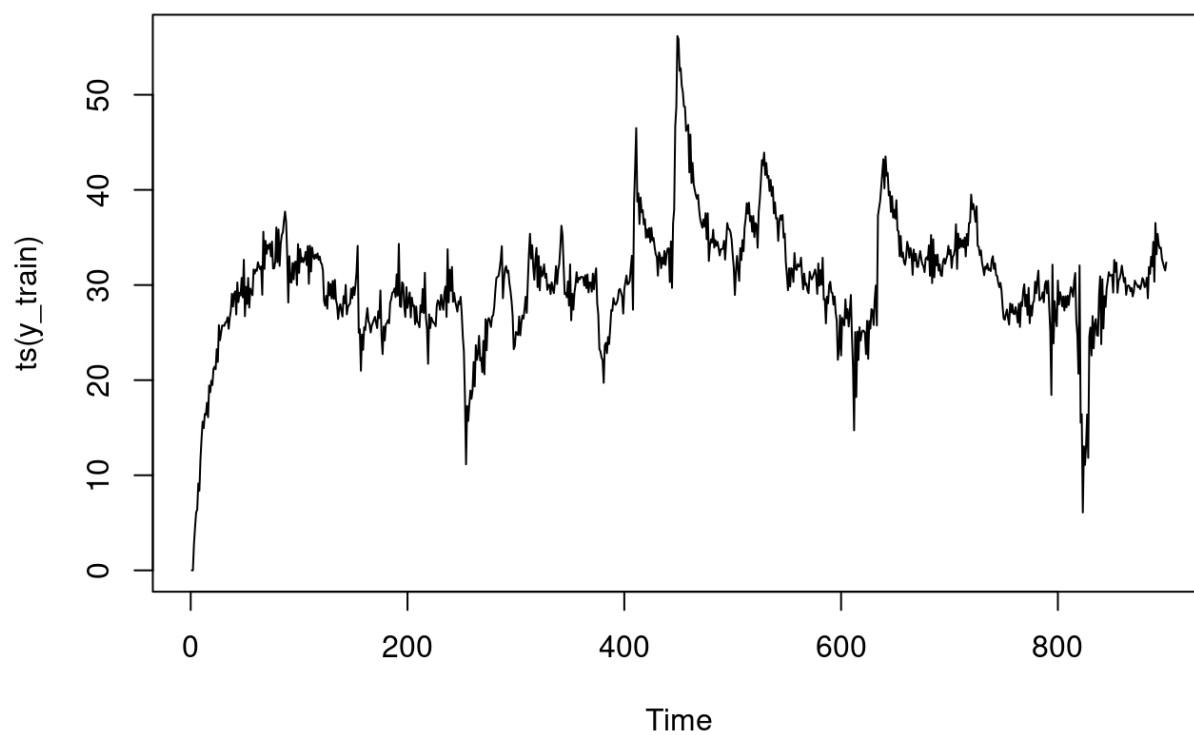
for (t in 3: (length(v)-1)){
  y[t]<- mu + phi1*y[t-1] +phi2*y[t-2]+ sqrt(sigma_squared[t])*v[t]
  y=append(y,y[t])
}
#####Train&Test Split#####
n <- length(y)
n.train <- floor(n*0.90)
n.test <- n-n.train

y_train<- y[1:n.train]
y_test<-tail(y,n.test)

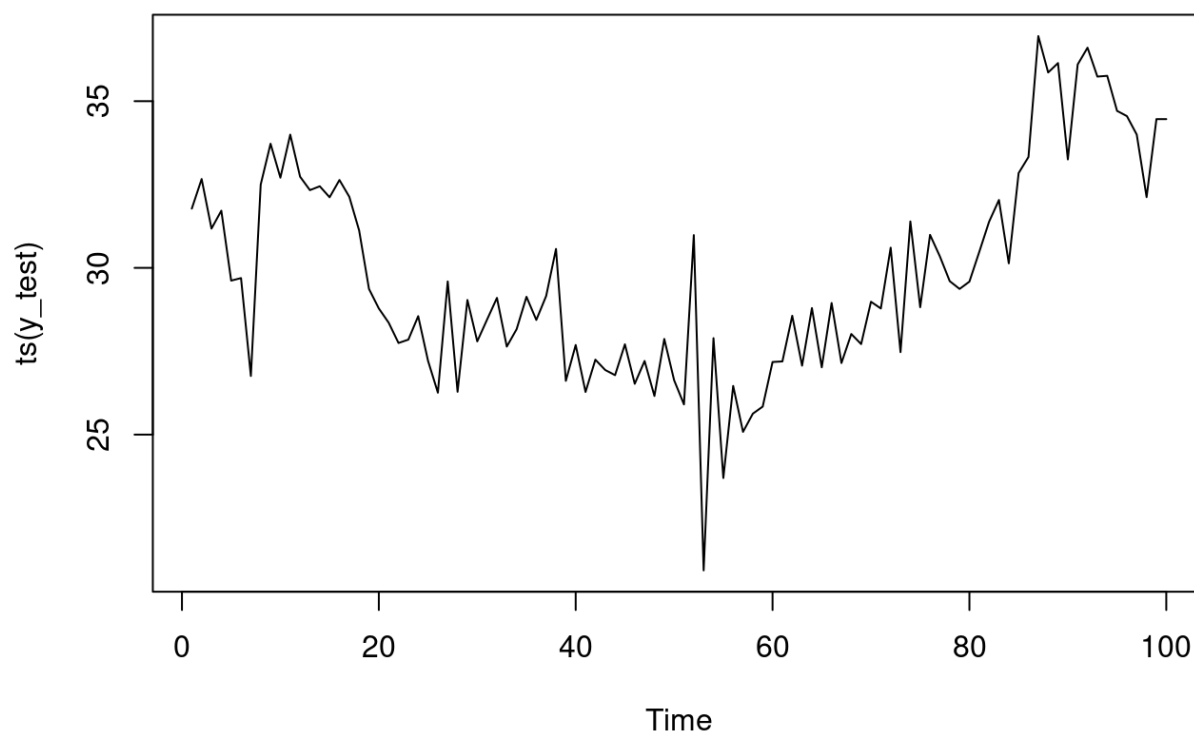
library(forecast)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
#plot of y_train & y_test vs t
plot(ts(y_train))
```



```
plot(ts(y_test))
```

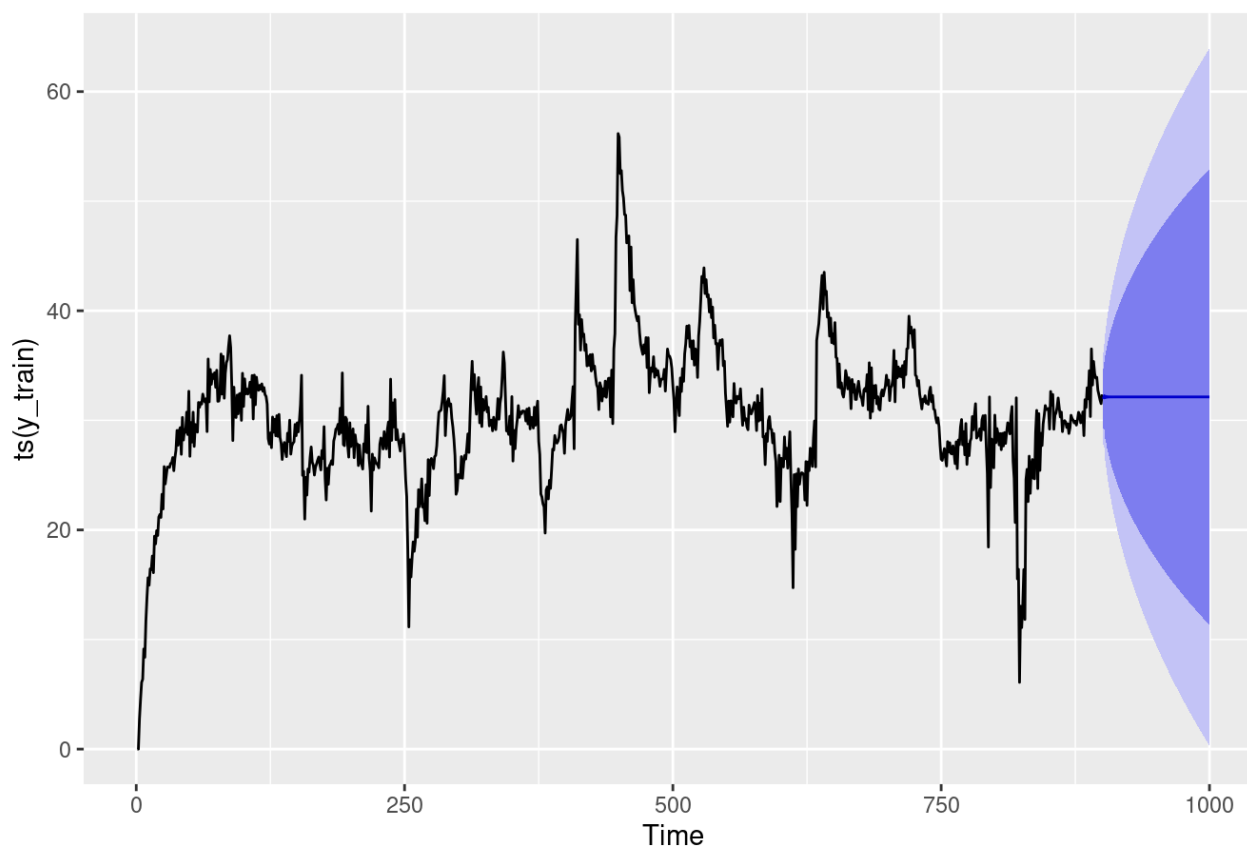


```
# fitting arima model using auto.arima
mod1=auto.arima(ts(y_train))
summary(mod1)
```

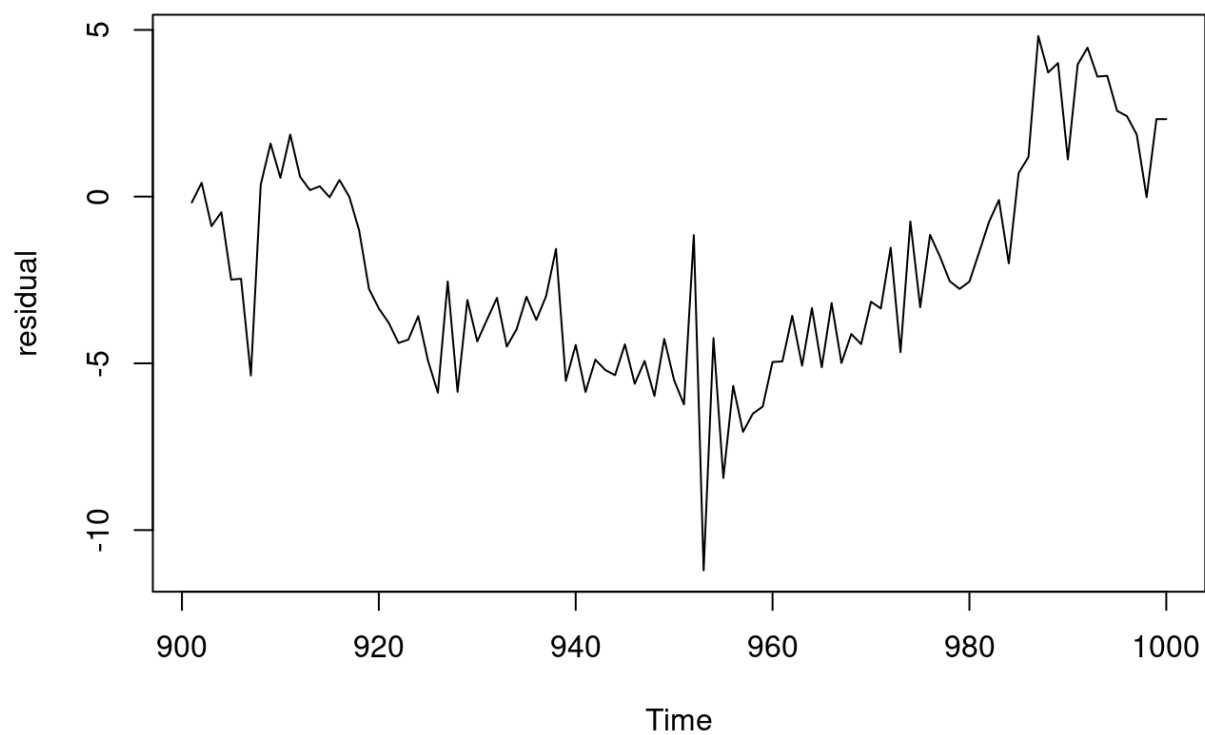
```
## Series: ts(y_train)
## ARIMA(2,1,0)
##
## Coefficients:
##          ar1      ar2
##       -0.4365  0.1346
## s.e.   0.0330  0.0330
##
## sigma^2 = 4.449: log likelihood = -1945.71
## AIC=3897.41  AICc=3897.44  BIC=3911.82
##
## Training set error measures:
##              ME    RMSE      MAE        MPE      MAPE      MASE
## Training set 0.04646258 2.105649 1.447756 -0.007362186 5.480612 0.8447357
##              ACF1
## Training set -0.002973327
```

```
predicted= forecast(mod1,100)
autoplot(predicted)
```

Forecasts from ARIMA(2,1,0)

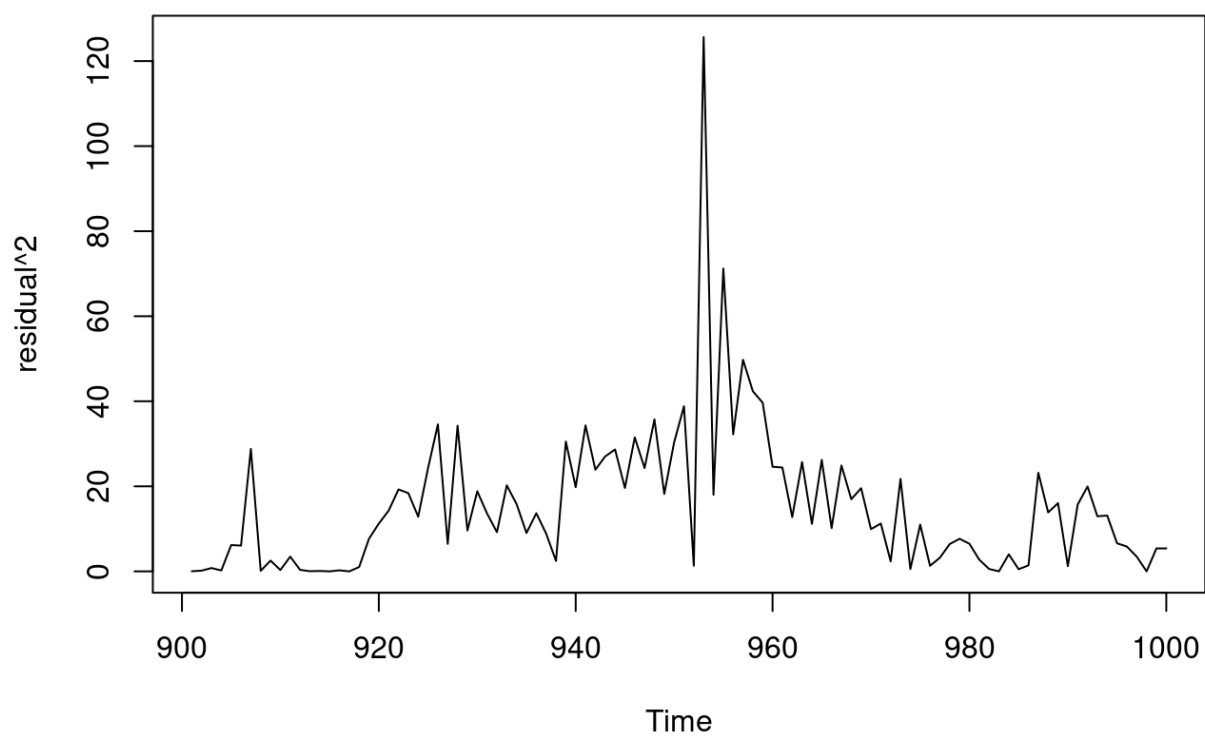


```
# ut plot
residual= y_test-predicted$mean
plot(residual)
```

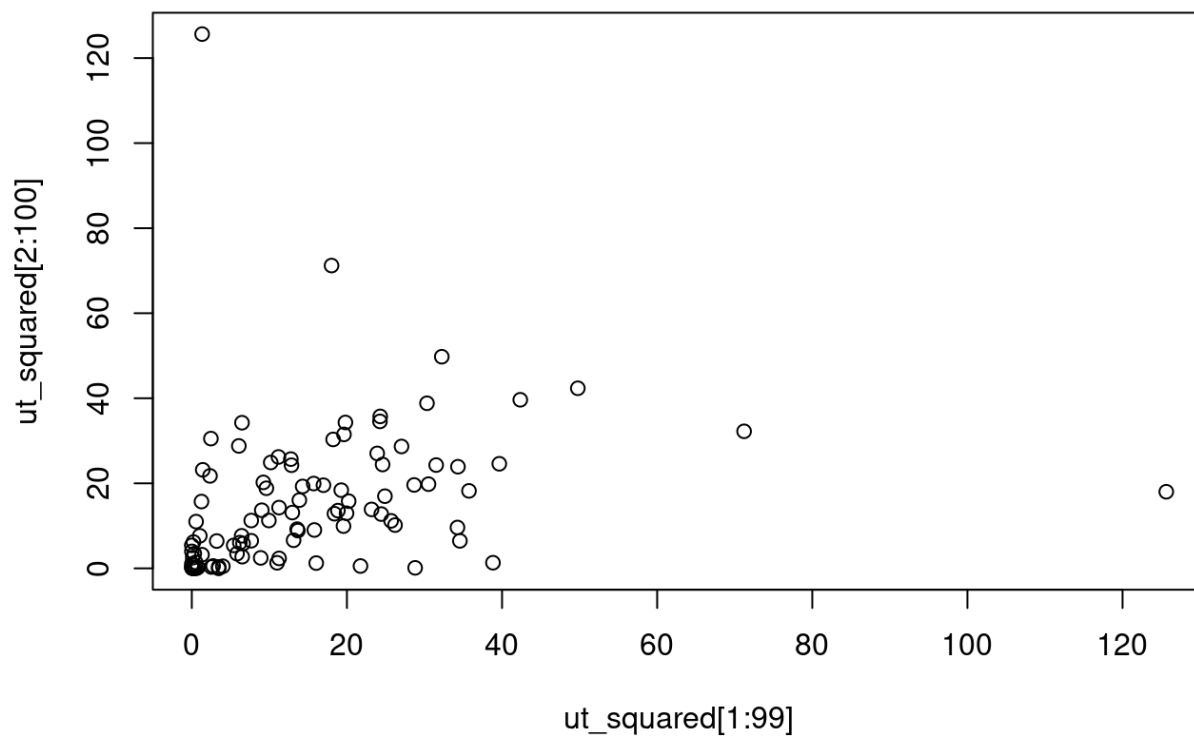


```
#ut^2 plot
```

```
plot(residual^2)
```



```
#ut^2 vs u(t-1)^2 plot  
ut_squared<-residual^2  
plot(ut_squared[1:99],ut_squared[2:100])
```



```
## forecasting error for the test set  
sqrt(sum((predicted$mean-y_test )^2)/n.test)
```

```
## [1] 3.909574
```

```
#Value = 3.909574

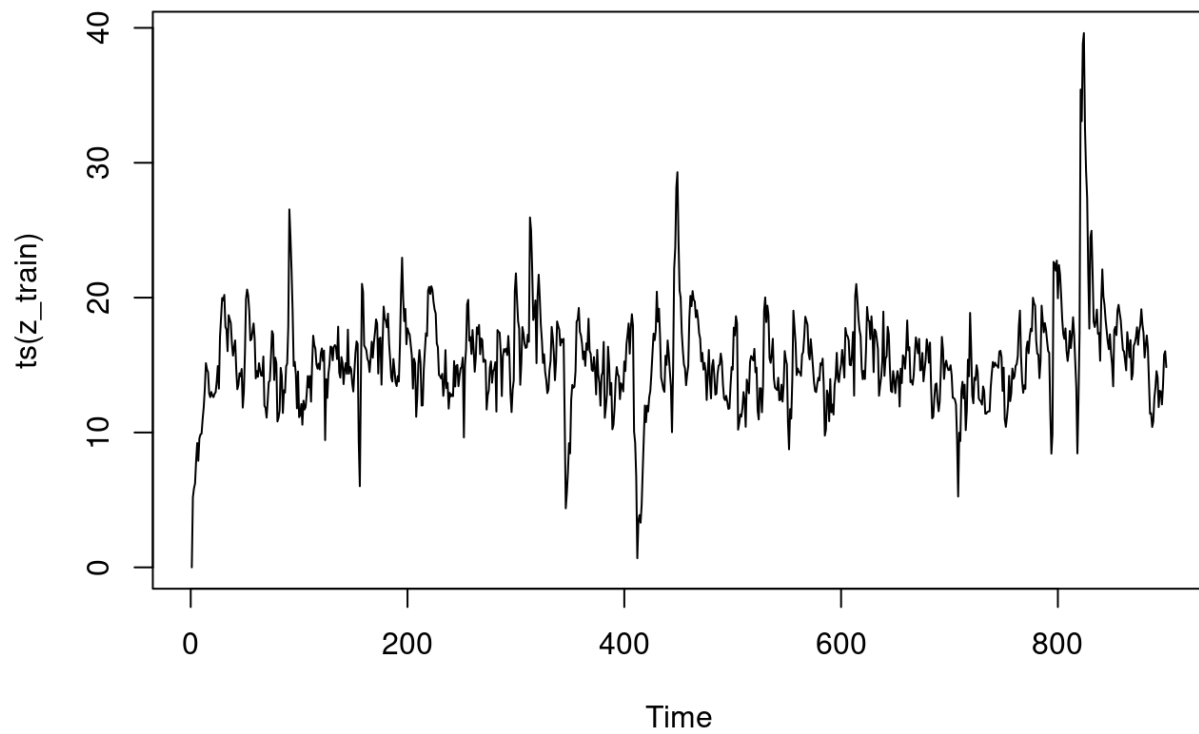
#Simulation Exercise : 2
mu<-3
phi1<-0.8
zeta=1
alpha1=0.5
delta1=0.3
z=c()
z[1]=0
w=rnorm(1000,mean=0,sd=1)
sigma_square=c()
sigma_square[1]=0.1
for (t in 2:(length(w)-2)){
  sigma_square[t]= zeta + alpha1*(sigma_square[t-1]*w[t-1]*w[t-1]) + delta1*sigma_square[t-1]
  sigma_square=append(sigma_square,sigma_square[t])
}
# generating the time series

for (t in 2: (length(w)-1)){
  z[t]<- mu + phi1*z[t-1] + sqrt(sigma_squared[t])*w[t]
  z=append(z,z[t])
}

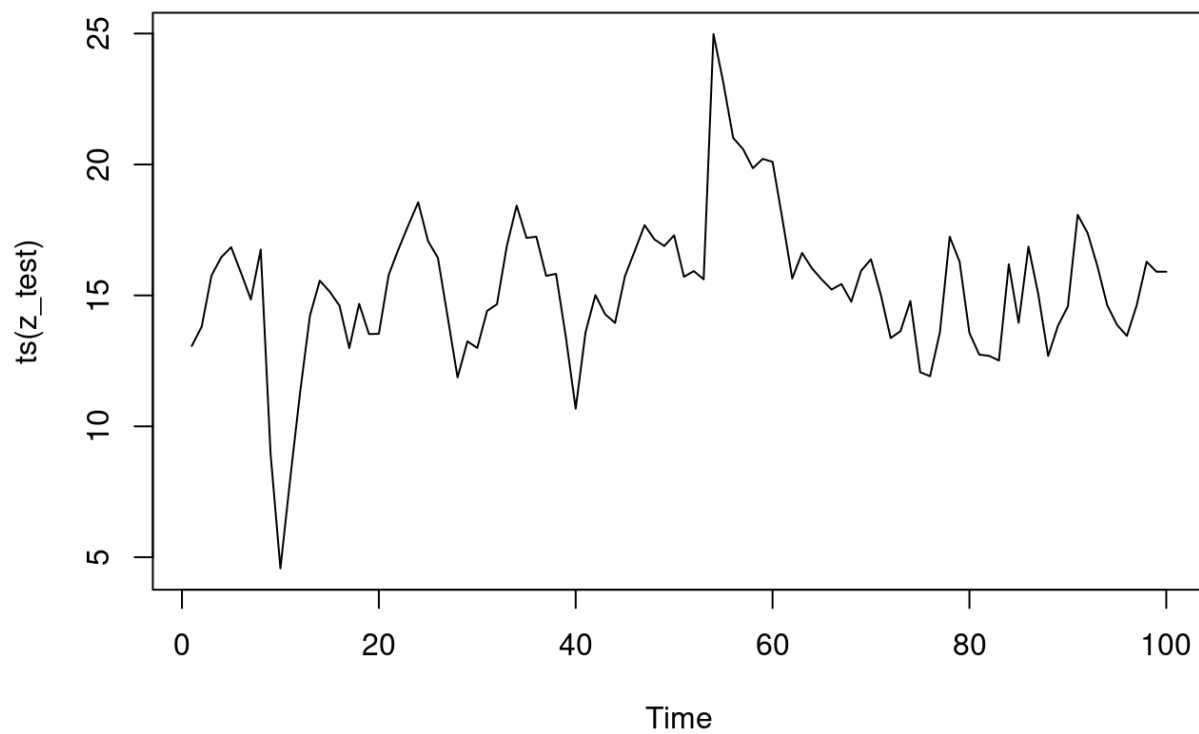
#####Train&Test Split#####
n <- length(z)
n.train <- floor(n*0.90)
n.test <- n-n.train

z_train<- z[1:n.train]
z_test<-tail(z,n.test)

library(forecast)
#plot of y_train & y_test vs t
plot(ts(z_train))
```



```
plot(ts(z_test))
```



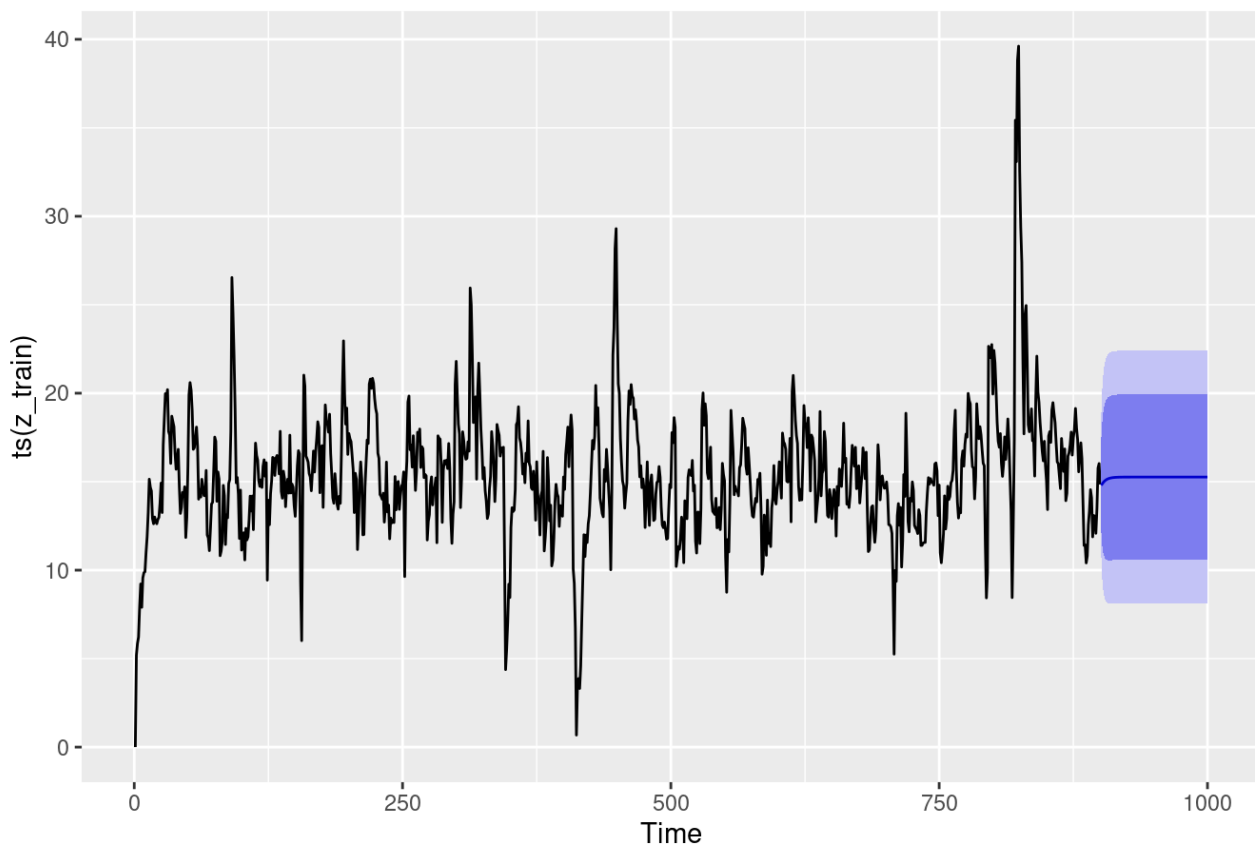
```
# fitting arima model using auto.arima
mod2=auto.arima(ts(z_train))
summary(mod2)
```

```
## Series: ts(z_train)
## ARIMA(2,0,0) with non-zero mean
##
## Coefficients:
##          ar1      ar2      mean
##          0.9161 -0.1088 15.2616
## s.e.  0.0333  0.0335  0.3510
##
## sigma^2 = 4.164: log likelihood = -1918.08
## AIC=3844.15  AICc=3844.2  BIC=3863.36
##
## Training set error measures:
##              ME      RMSE      MAE  MPE  MAPE      MASE      ACF1
## Training set 0.01727332 2.037262 1.368718 -Inf  Inf  0.9231791 -0.02085793
```

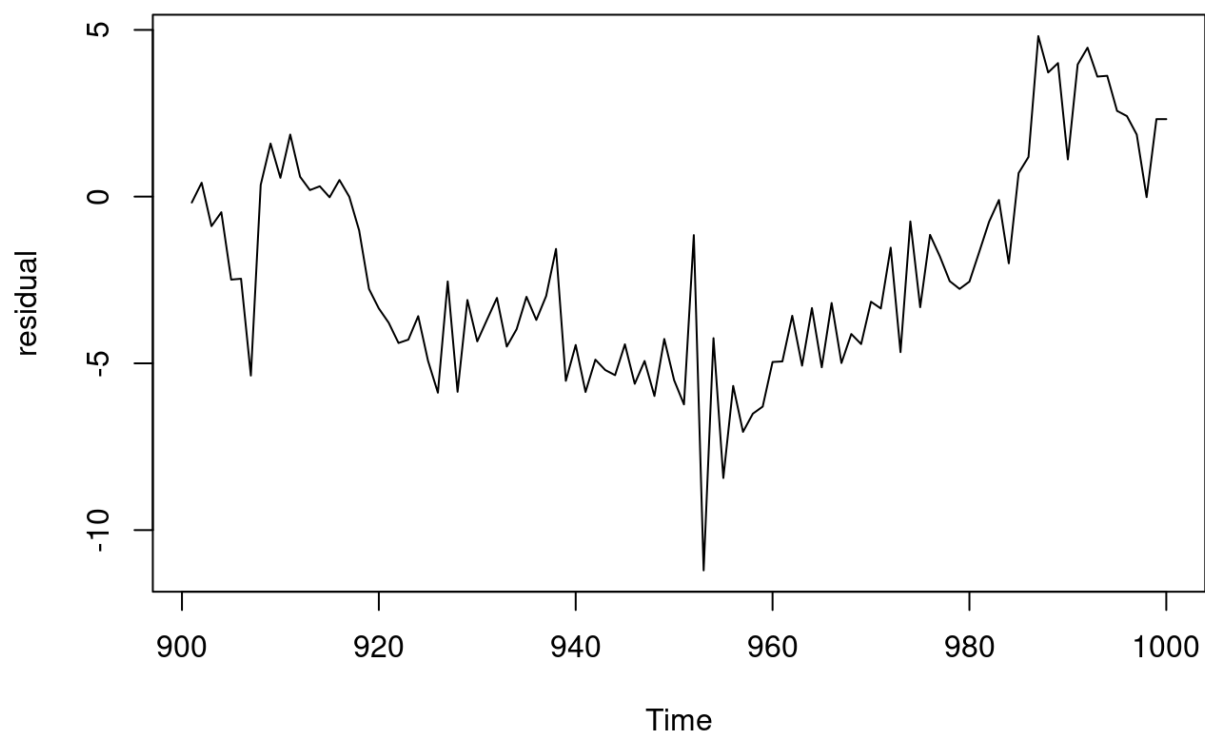
```
predicted_new= forecast(mod2,100)
```

```
autoplot(predicted_new)
```

Forecasts from ARIMA(2,0,0) with non-zero mean

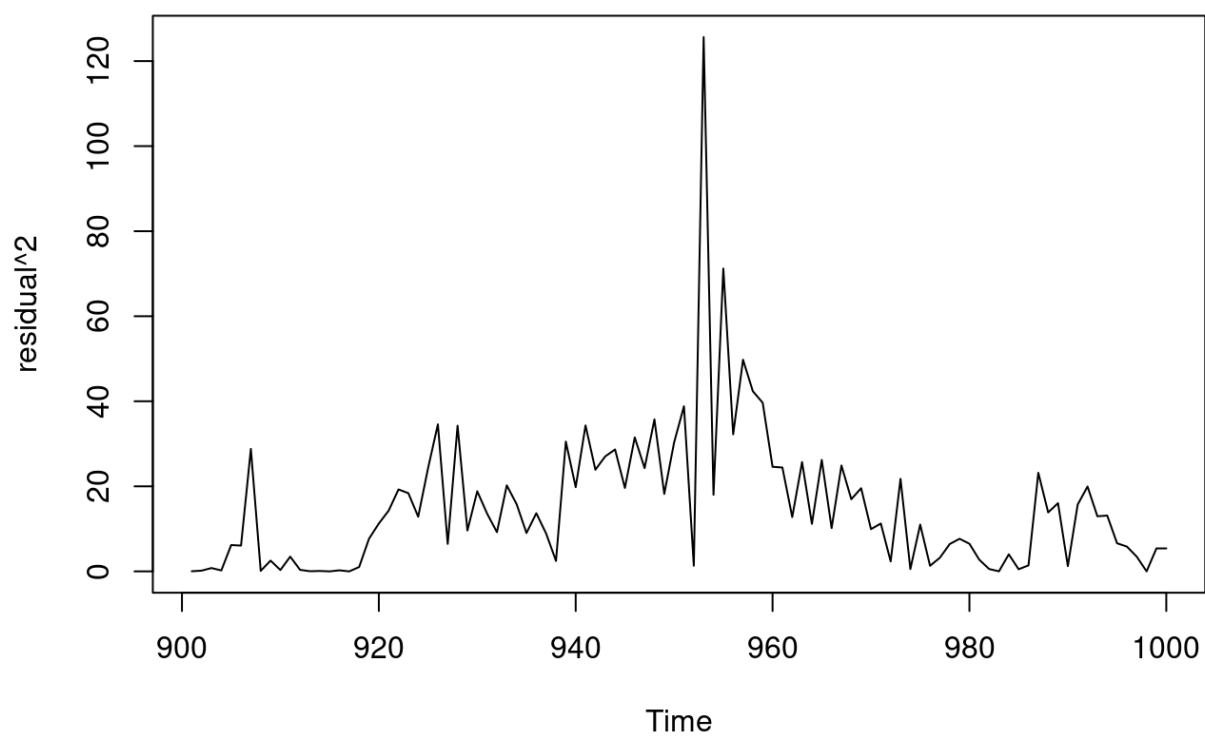


```
# ut plot
residual_new= z_test-predicted_new$mean
plot(residual)
```

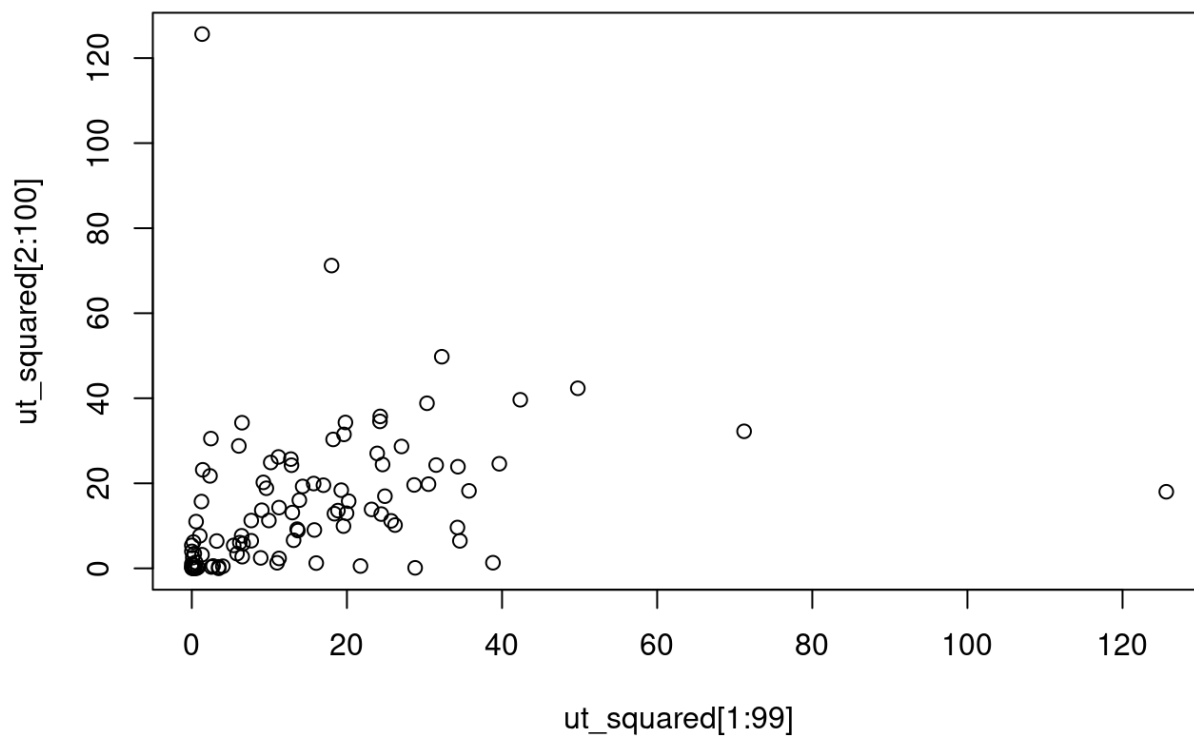



```
#ut^2 plot
```

```
plot(residual^2)
```



```
#ut^2 vs u(t-1)^2 plot  
ut_squared<-residual^2  
plot(ut_squared[1:99],ut_squared[2:100])
```



```
## forecasting error for the test set  
sqrt(sum((predicted_new$mean-z_test )^2)/n.test)
```

```
## [1] 2.748975
```

```
#Value = 2.512857
```