

ARMA-GARCH

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1 Data

1.1 Data Source

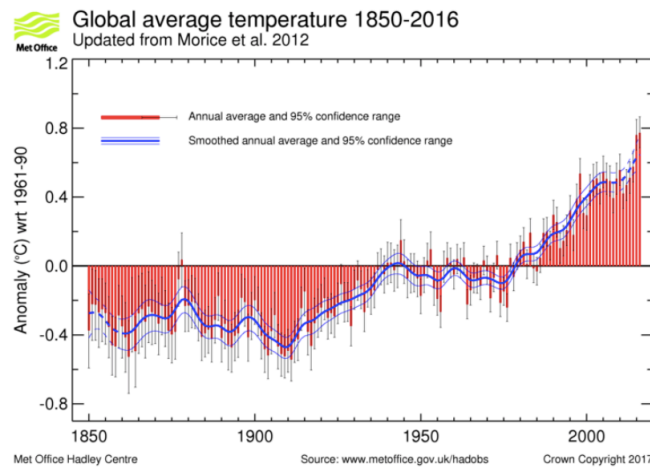
HadCRUT4 is a gridded dataset of global historical surface temperature anomalies relative to a 1961-1990 reference period. Data are available for each month since January 1850, on a 5 degree grid. The dataset is a collaborative product of the Met Office Hadley Centre and the Climatic Research Unit at the University of East Anglia.

`url = http://www.metoffice.gov.uk/hadobs/hadcrut4/data/current/time_series/HadCRUT.4.5.0.0.monthly_ns_avg.txt.`

1.2 Brief Data Description

The gridded data are a blend of the CRUTEM4 land-surface air temperature dataset and the HadSST3 sea-surface temperature (SST) dataset. The dataset is presented as an ensemble of 100 dataset realisations that sample the distribution of uncertainty in the global temperature record given current understanding of non-climatic factors affecting near-surface temperature observations. This ensemble approach allows characterisation of spatially and temporally correlated uncertainty structure in the gridded data, for example arising from uncertainties in methods used to account for changes in SST measurement practices, homogenisation of land station records and the potential impacts of urbanisation. The HadCRUT4 data are neither interpolated nor variance adjusted.

Below is a graph provided by www.metoffice.gov.uk:



1.3 Loading the Data into R

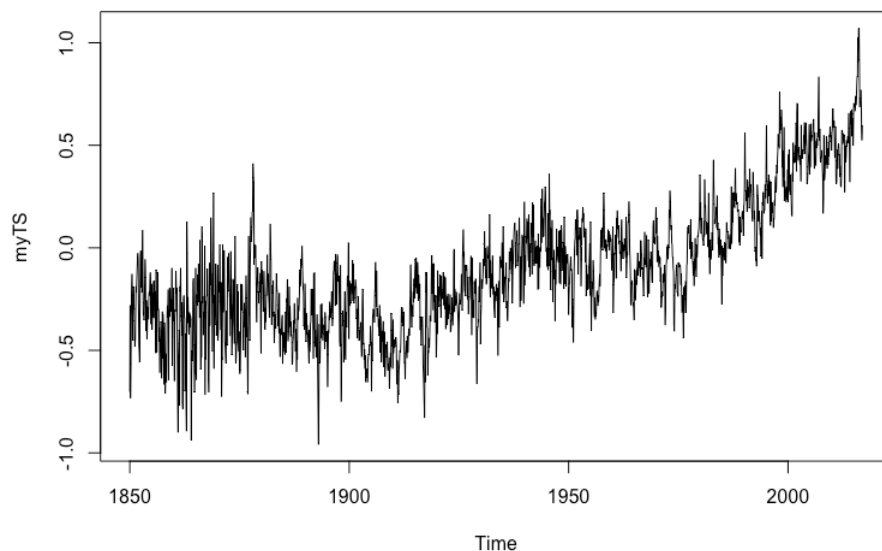
For our purpose, we are not interested in the spatial distribution, so we only use the *Global Mean*.

Loading the data into R:

```
library(curl)
tmpf <- tempfile()
curl_download(url, tmpf)
gtemp <- read.table(tmpf)[, 1:2]
temp = gtemp$V2[1:2004]
```

We only use the first two columns: *time and monthly global mean*. We pick the first 2004 observations, which is monthly data from 1850 ~ 2016, so that the data has complete periods.

The time series of *temp* is shown below:



2 Dealing with the time series

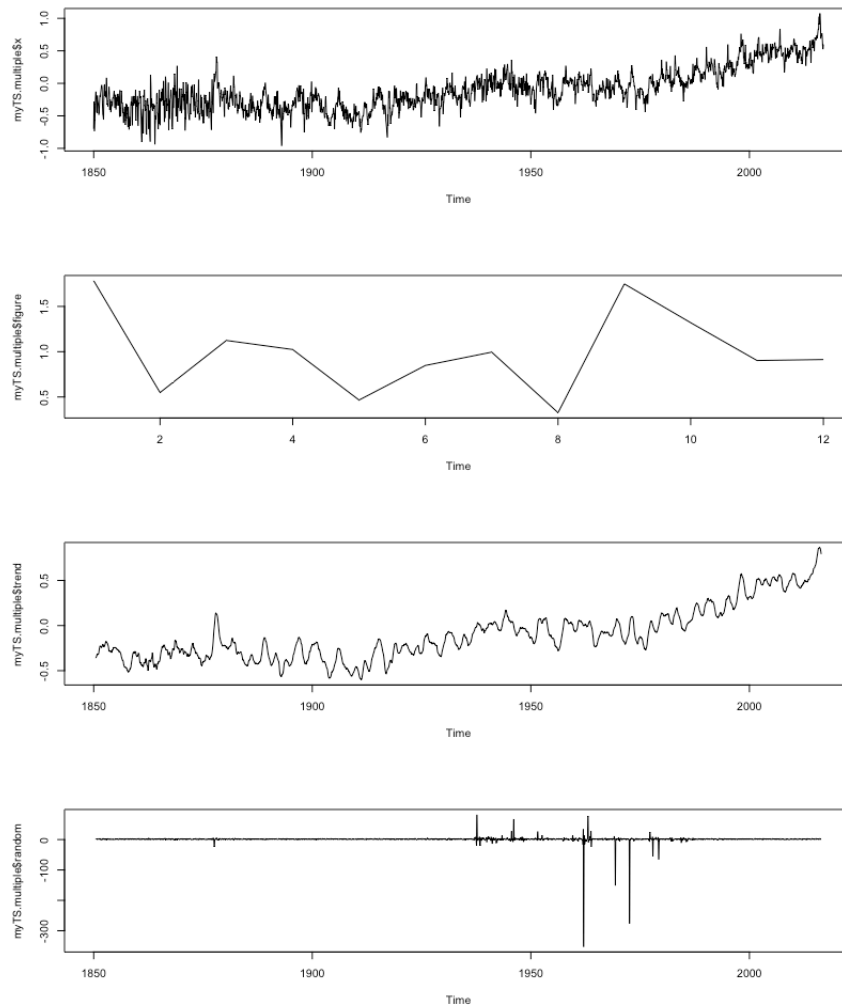
2.1 Decompose

The first thing we might want to do is to wipe out the seasonal component. There're many approaches to do it in R. We choose to use the *decompose()* provided by *{stats}*.

Looking at the time series, we think a additive model should be appropriate.

We can quickly checked that multiplicative model is not appropriate:

Figure 1: multiplicative model: original ts, seasonal component, time trend, residuals



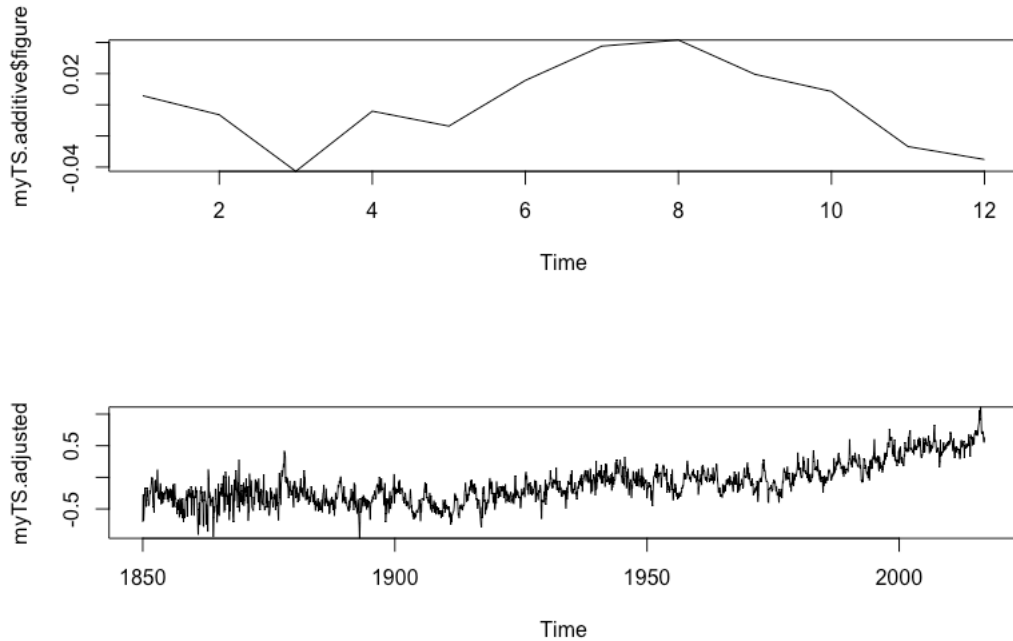
Obviously the random term is not easy to be modelled.

Therefore, decompose the time series with additive method in the following code:

```
library(TSA)
myTS = ts(as.numeric(temp), start = c(1850, 1), frequency = 12)
myTS.additive = decompose(myTS)
myTS.adjusted = myTS.additive$x - myTS.additive$seasonal
```

The *myTS.adjusted* now is free of seasonal components. The following graph illustrate the components.

Figure 2: additive model: seasonal component, adjusted series



Obviously, the time series is not stationary. For simplicity, use `diff()`.

```
dtemp = diff(myTS.adjusted)
```

```
> adf.test(dtemp)
```

Augmented Dickey-Fuller Test

```
data: dtemp
```

```
Dickey-Fuller = -16.175, Lag order = 12, p-value = 0.01
```

```
alternative hypothesis: stationary
```

So we can convince ourself that the time series *dtemp* is stationary.

2.2 Build a $ARMA(p, q)$ for *dtemp*

For simplicity, we use `auto.arima()` from `{forecast}` to judge the order.

```
library(forecast)
```

```
> auto.arima(dtemp> auto.arima(dtemp)
```

```
Series: dtemp
```

```
ARIMA(2,0,4)(2,0,1)[12] with non-zero mean
```

```
Coefficients:
```

```
ar1      ar2      ma1      ma2      ma3      ma4      sar1      sar2      sma1      mean
```

	0.5041	0.3585	-1.0458	-0.1600	0.1362	0.0780	0.7619	0.0779	-0.7884	5e-04
s.e.	0.2431	0.2142	0.2423	0.3481	0.1082	0.0257	0.0926	0.0248	0.0910	2e-04

sigma^2 estimated as 0.01428: log likelihood=1417.03

AIC=-2812.05 AICc=-2811.92 BIC=-2750.43

first find the possible orders might be arma(2, 1) or arma(2, 4)

arma21.dtemp = arima(dtemp, c(2, 0, 1))

arma24.dtemp = arima(dtemp, c(2, 0, 4))

next examine the two models' residuals

> auto.arima(arma21.dtemp\$residuals)

Series: arma21.dtemp\$residuals

ARIMA(2,0,3)(2,0,1)[12] with zero mean

Coefficients:

	ar1	ar2	ma1	ma2	ma3	sar1	sar2	sma1
	1.5859	-0.6762	-1.6089	0.6706	0.0506	0.7454	0.0748	-0.7785
s.e.	0.1156	0.1065	0.1169	0.1264	0.0297	0.1209	0.0258	0.1181

sigma^2 estimated as 0.01429: log likelihood=1415.92

AIC=-2813.83 AICc=-2813.74 BIC=-2763.41

> auto.arima(arma24.dtemp\$residuals)

Series: arma24.dtemp\$residuals

ARIMA(0,0,0) with zero mean

sigma^2 estimated as 0.01435: log likelihood=1408.31

AIC=-2814.63 AICc=-2814.62 BIC=-2809.02

Therefore it should be appropriate to choose *arma(2, 4)* for series *dtemp*.

my.arma = arma24.dtemp

> my.arma

Call:

arima(x = dtemp, order = c(2, 0, 4))

Coefficients:

	ar1	ar2	ma1	ma2	ma3	ma4	intercept
	0.5204	0.3247	-1.0536	-0.1269	0.1168	0.0755	5e-04
s.e.	0.2733	0.2356	0.2727	0.3828	0.1117	0.0265	2e-04

sigma^2 estimated as 0.01435: log likelihood = 1407.67, aic = -2801.34

```
res = my.arma$residuals

> Box.test(res, type = 'Ljung-Box')

Box-Ljung test

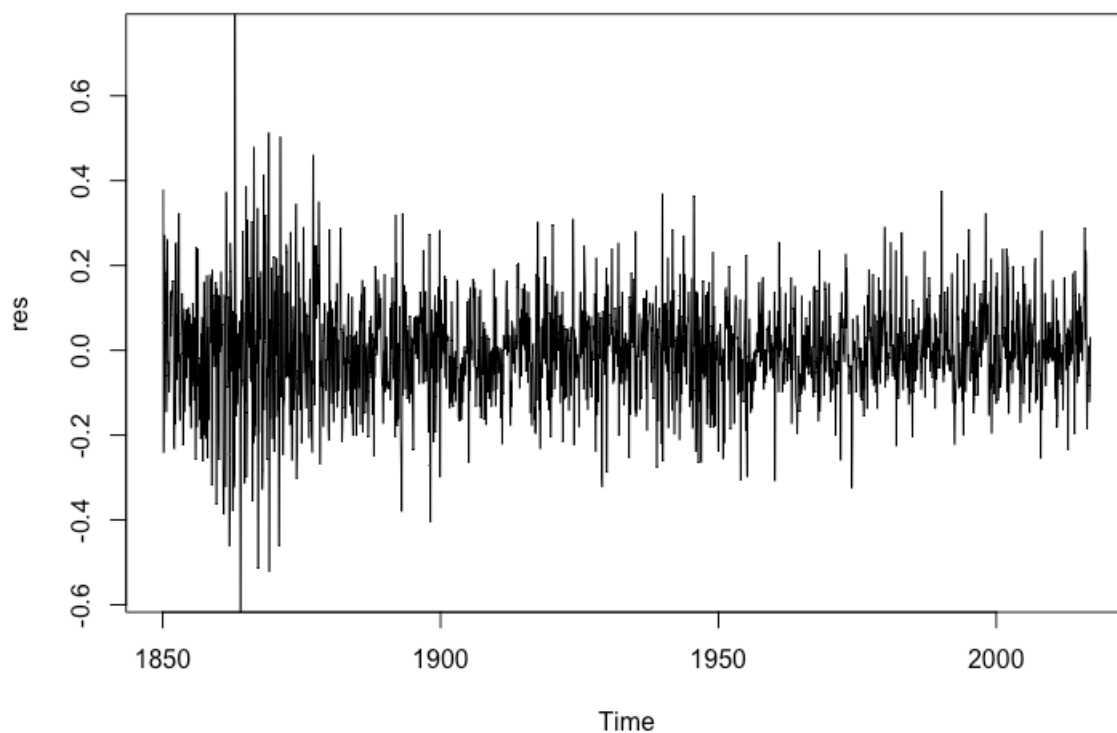
data:  res
X-squared = 0.0058853, df = 1, p-value = 0.9388
```

The $ARMA(2,4)$ success in making the arma residual independent.

2.3 GARCH

One can be pretty satisfied with the results right now. Yet Looking at the plot of arma residual:

Figure 3: arma residual



It makes us wondering if it has $ARCH$ effect. Using *arch.test* from *{aTSA}* to perform the $LM - Test$:

```
library(aTSA)
```

```
> arch.test(my.arma)
ARCH heteroscedasticity test for residuals
alternative: heteroscedastic
```

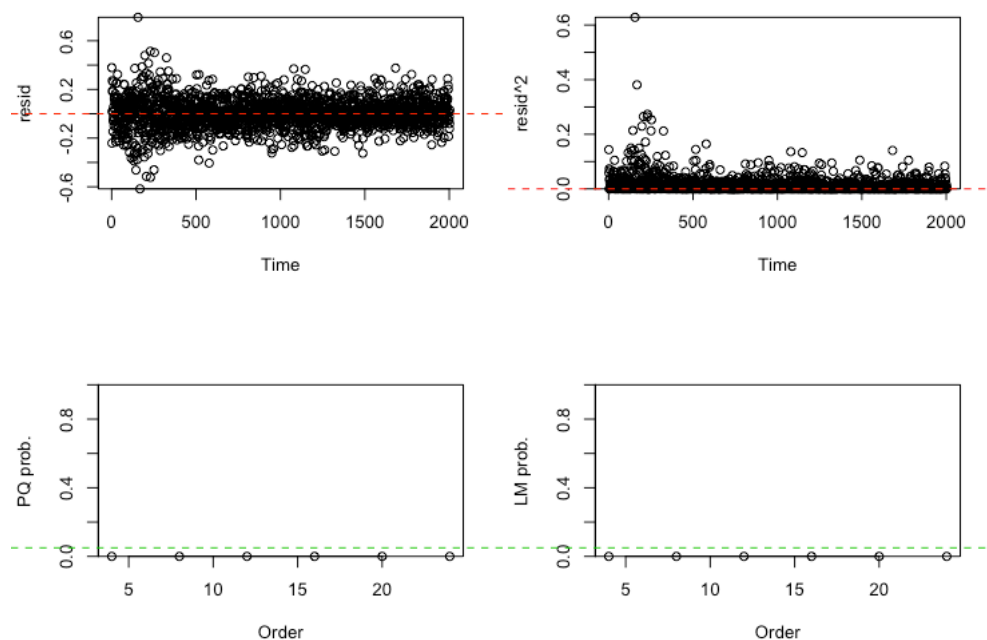
Portmanteau-Q test:

	order	PQ	p.value
[1,]	4	99.4	0
[2,]	8	116.9	0
[3,]	12	411.5	0
[4,]	16	475.6	0
[5,]	20	495.9	0
[6,]	24	755.8	0

Lagrange-Multiplier test:

	order	LM	p.value
[1,]	4	1418	0
[2,]	8	697	0
[3,]	12	418	0
[4,]	16	212	0
[5,]	20	168	0
[6,]	24	137	0

Figure 4: arma residual



It supports our doubt. Therefore we have the motive to build a *GARCH* model. We decide to use the package *rugarch*.

A standard GARCH model has the following variance equation:

$$\sigma_t^2 = (w + \sum_{j=1}^m \zeta_j v_{jt}) + \sum_{j=1}^q \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2$$

So we wrote a function:

```
library(rugarch)
my_sGARCH_test <- function(p, q, m, n, ts.data = res)
{
# I use include.mean = FALSE after trying TRUE
# to find out insignificance
  myspec=ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(p, q)),
    mean.model = list(armaOrder = c(m, n), include.mean = FALSE),
    distribution.model = "norm")
  myfit=ugarchfit(myspec,data=ts.data, solver="solnp")
  return(myfit)
}
```

After trying a few times from (1,0), (0,0,0) to (5,5), (4,0,4), *GARCH(1,1)*, *ARIMA(2, 0, 3)* is the most satisfying model. Here we realize that using GARCH model, the order of ARIMA might changes.

```
fit1 = my_sGARCH_test(1, 1, 2, 3, dtemp)
```

```
> fit1
```

```
*-----*
*           GARCH Model Fit           *
*-----*
```

```
Conditional Variance Dynamics
```

```
-----
GARCH Model : sGARCH(1,1)
```

```
Mean Model : ARFIMA(2,0,3)
```

```
Distribution : norm
```

```
Optimal Parameters
```

```
-----
      Estimate Std. Error   t value Pr(>|t|)
ar1    -0.090935   0.015226   -5.9724 0.000000
ar2     0.754333   0.015069   50.0583 0.000000
ma1    -0.391906   0.007313  -53.5917 0.000000
ma2    -0.863257   0.000130 -6647.5909 0.000000
ma3     0.295634   0.007800   37.9010 0.000000
omega   0.000082   0.000034    2.3956 0.016595
alpha1  0.023026   0.003614    6.3706 0.000000
```


beta1 0.970594 0.004705 206.2925 0.000000

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(> t)
ar1	-0.090935	0.017031	-5.3393	0.000000
ar2	0.754333	0.017312	43.5726	0.000000
ma1	-0.391906	0.002647	-148.0378	0.000000
ma2	-0.863257	0.000144	-6000.9074	0.000000
ma3	0.295634	0.002903	101.8443	0.000000
omega	0.000082	0.000036	2.2838	0.022382
alpha1	0.023026	0.003636	6.3329	0.000000
beta1	0.970594	0.003734	259.9413	0.000000

LogLikelihood : 1512.336

Information Criteria

Akaike -1.5021
Bayes -1.4797
Shibata -1.5021
Hannan-Quinn -1.4939

Weighted Ljung-Box Test on Standardized Residuals

statistic p-value
Lag[1] 0.3742 0.5407
Lag[2*(p+q)+(p+q)-1][14] 4.5219 1.0000
Lag[4*(p+q)+(p+q)-1][24] 13.5547 0.3236
d.o.f=5
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals

statistic p-value
Lag[1] 31.06 2.506e-08
Lag[2*(p+q)+(p+q)-1][5] 37.84 1.904e-10
Lag[4*(p+q)+(p+q)-1][9] 51.28 4.433e-13
d.o.f=2

Weighted ARCH LM Tests

Statistic Shape Scale P-Value
ARCH Lag[3] 0.004507 0.500 2.000 9.465e-01
ARCH Lag[5] 11.085543 1.440 1.667 3.565e-03
ARCH Lag[7] 20.592184 2.315 1.543 4.509e-05

Nyblom stability test

Joint Statistic: 2.6294

Individual Statistics:

```
ar1    0.25019
ar2    0.61592
ma1    0.19513
ma2    0.24162
ma3    0.07259
omega  0.10095
alpha1 0.42035
beta1  0.20019
```

Asymptotic Critical Values (10% 5% 1%)

Joint Statistic: 1.89 2.11 2.59

Individual Statistic: 0.35 0.47 0.75

Sign Bias Test

	t-value	prob	sig
Sign Bias	0.3363	7.367e-01	
Negative Sign Bias	3.6815	2.380e-04	***
Positive Sign Bias	4.4421	9.396e-06	***
Joint Effect	33.2983	2.786e-07	***

Adjusted Pearson Goodness-of-Fit Test:

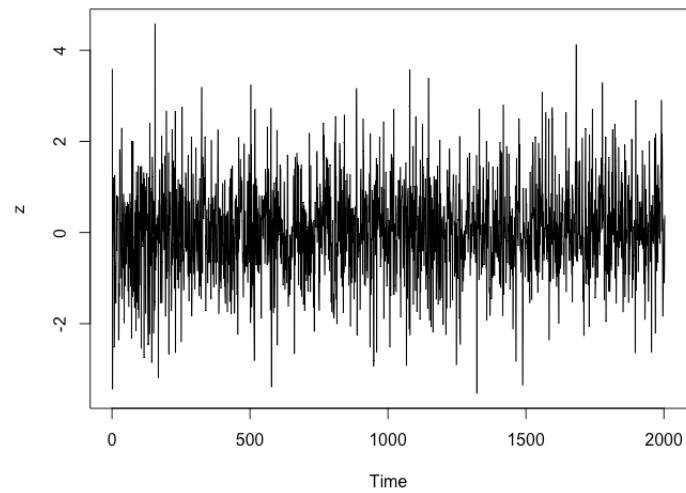
group	statistic	p-value(g-1)
1	20	57.32 1.019e-05
2	30	63.59 2.167e-04
3	40	85.01 2.883e-05
4	50	102.77 1.103e-05

Elapsed time : 0.365526

Substract the standardized(w.r.t. the variance model) residuals z , which is $z = \frac{residuals(\text{fit})}{sigma(\text{fit})}$.

```
z = residuals(fit1) / sigma(fit1)
plot.ts(z)
```

Figure 5: z

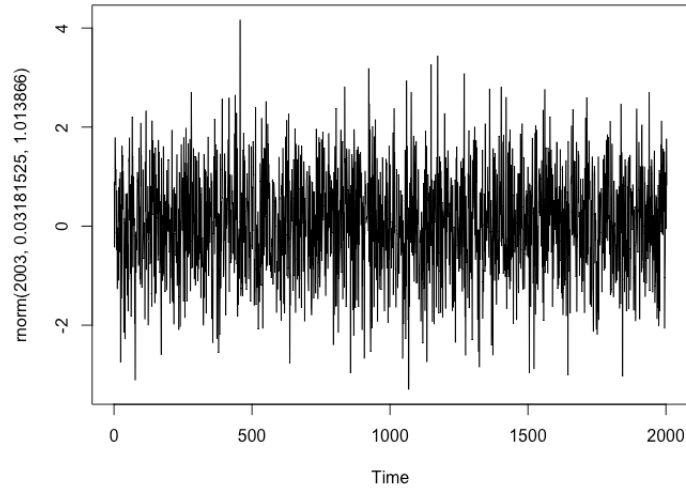


We can compute the mean and variance of z :

```
> mean(z)
[1] 0.03181525
> var(z)
[1] 1.013866
> length(z)
[1] 2003
> plot.ts(rnorm(2003, 0.03181525, 1.013866))
```

And then, just for fun, plot a normal sample series with the same parameters:

Figure 6: simulation of using rnorm



At least a human can't distinguish between them anymore. But what we most care about is whether standardized squared residuals can pass the *LM – Test*(subtracting from the above long result):

Weighted ARCH LM Tests

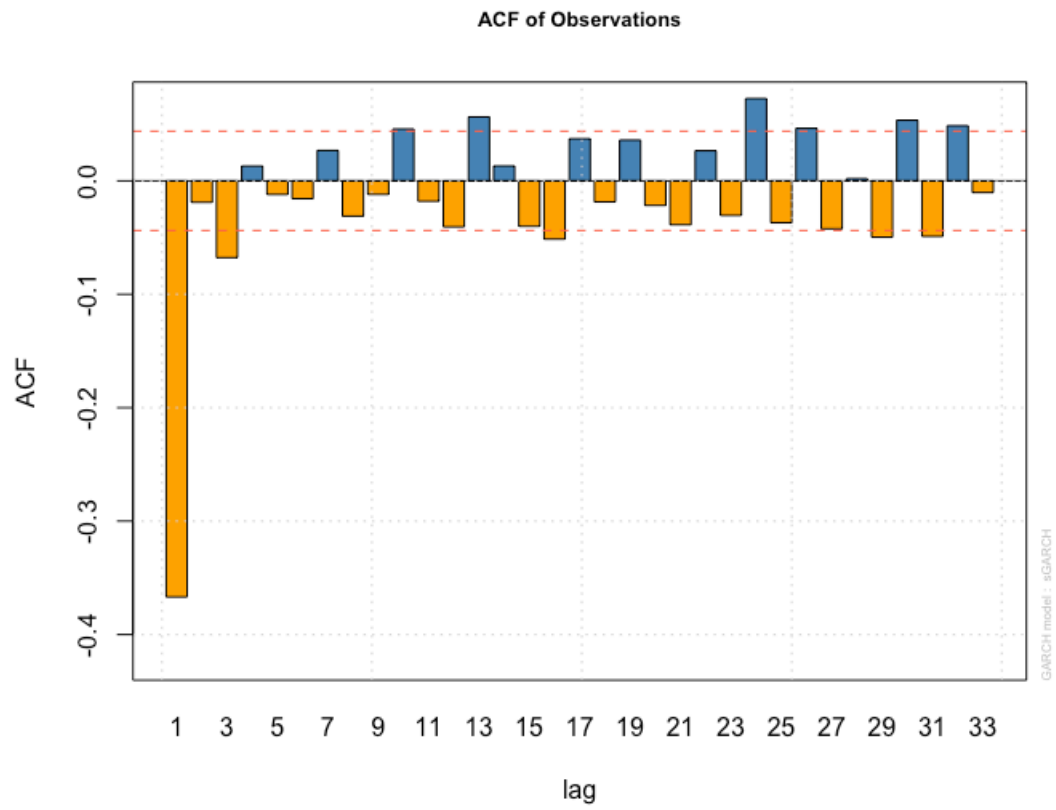
	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.004507	0.500	2.000	9.465e-01
ARCH Lag[5]	11.085543	1.440	1.667	3.565e-03
ARCH Lag[7]	20.592184	2.315	1.543	4.509e-05

We can see our model successfully wipes out ARCH effect at small lags, but fails at larger lags. This is the best 'sGARCH' can give with respect to our data. Maybe we should try long memory models instead of *diff()* at first.

Graphical Diagnostics:

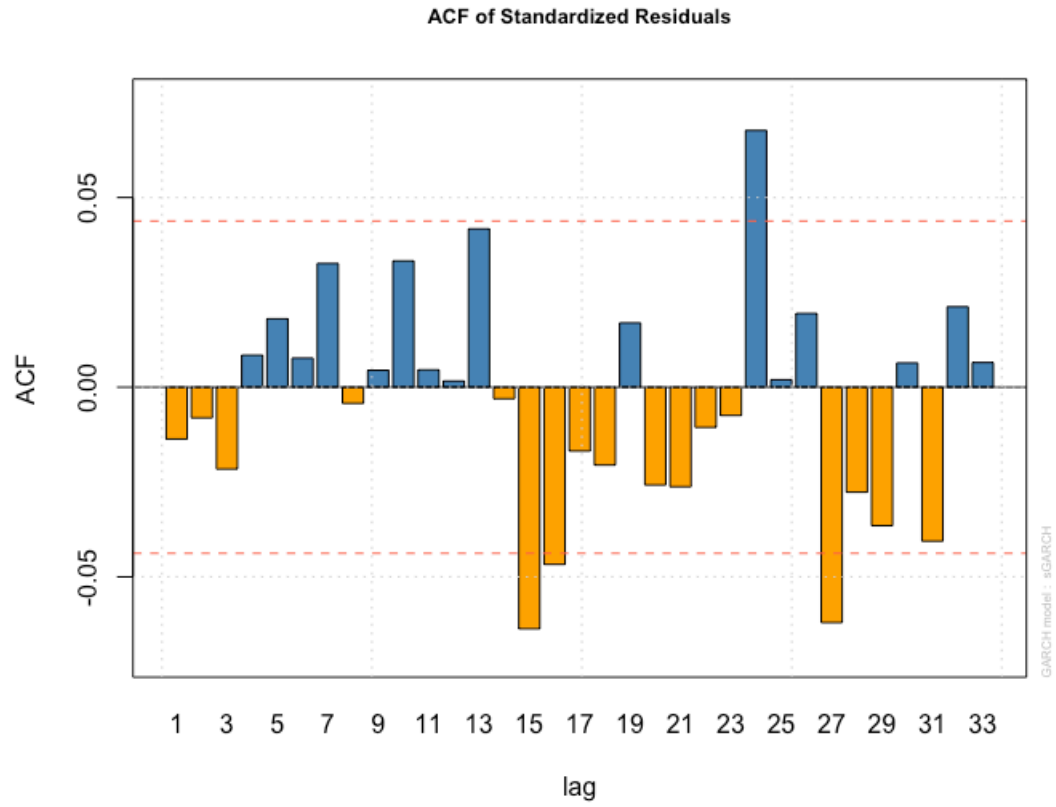
The original series' acf is shown below(the difference of temperature):

Figure 7: $\text{acf}(\text{dtemp})$



The acf of standardized residuals:

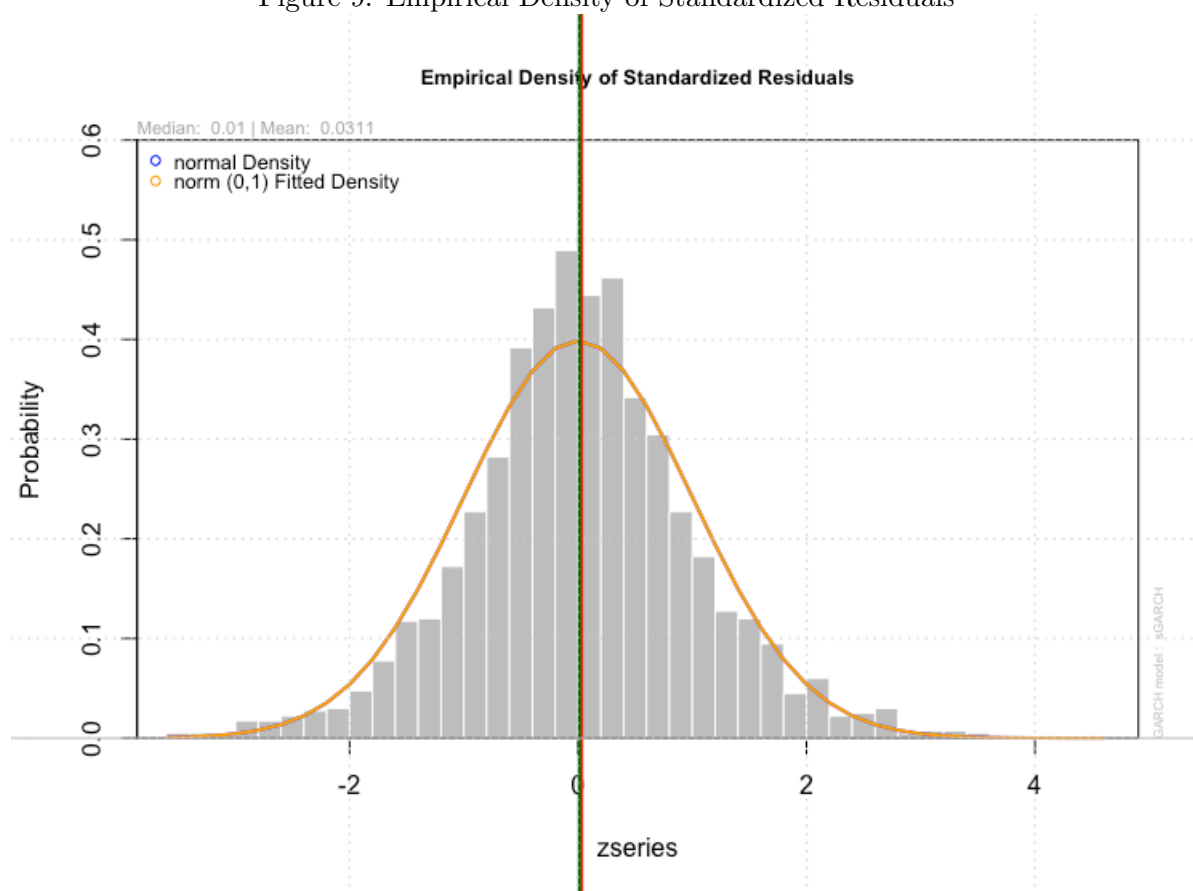
Figure 8: $\text{acf}(z)$



This is a prove that we should have used a long memory model.

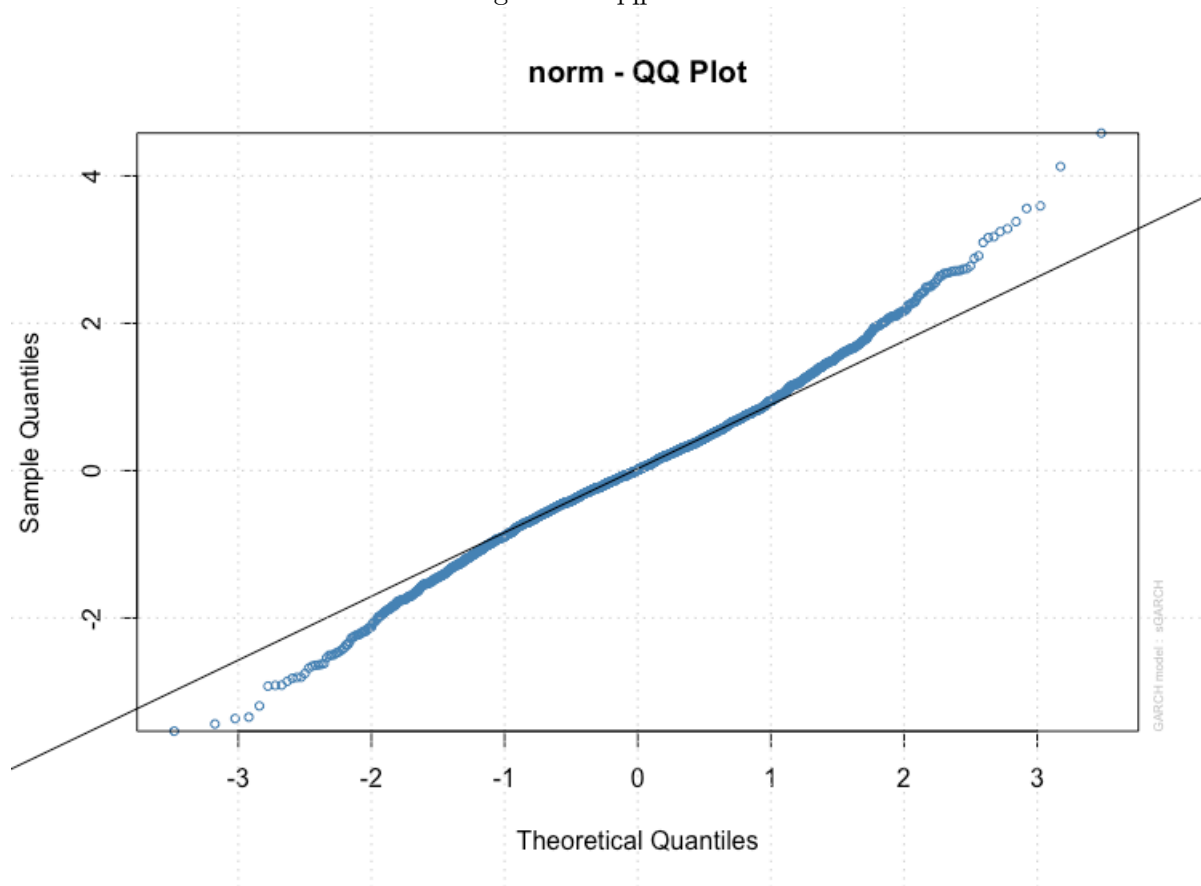
The *Empirical Density of Standardized Residuals* compared to normal distribution:

Figure 9: Empirical Density of Standardized Residuals

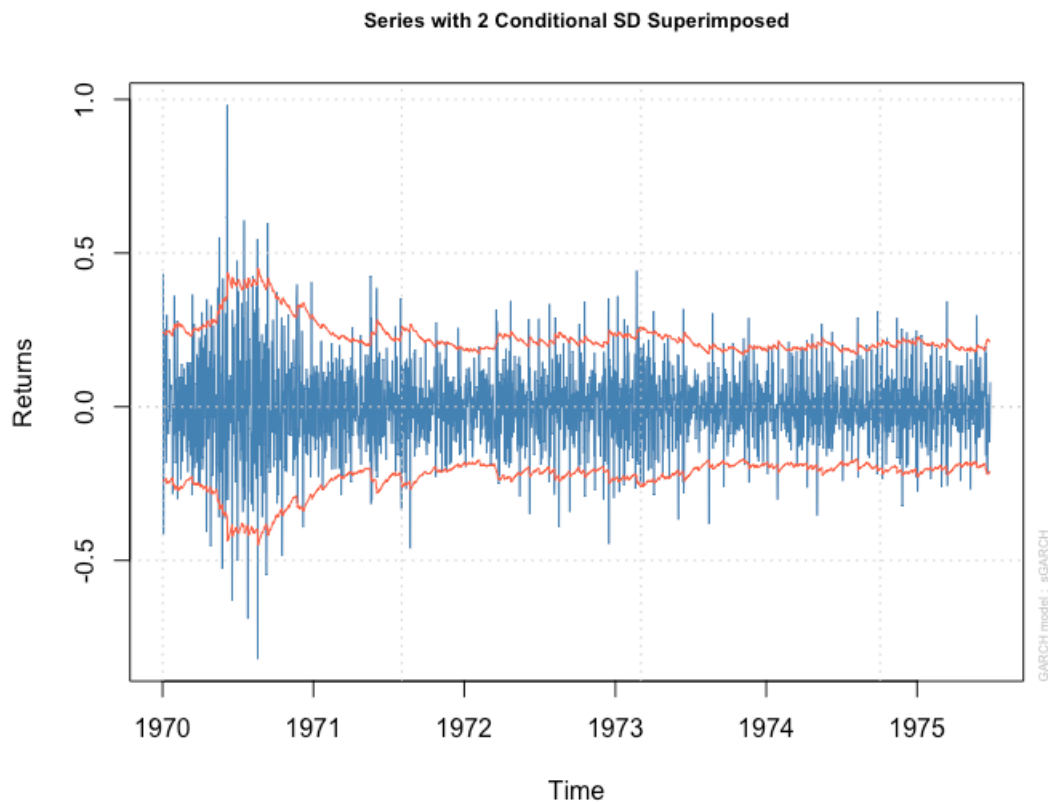


qqplot:

Figure 10: qqplot of z



We can see that z is skewed, which might be correlated with long lags' heterodasticity. Series with 2 Conditional SD Superimposed:

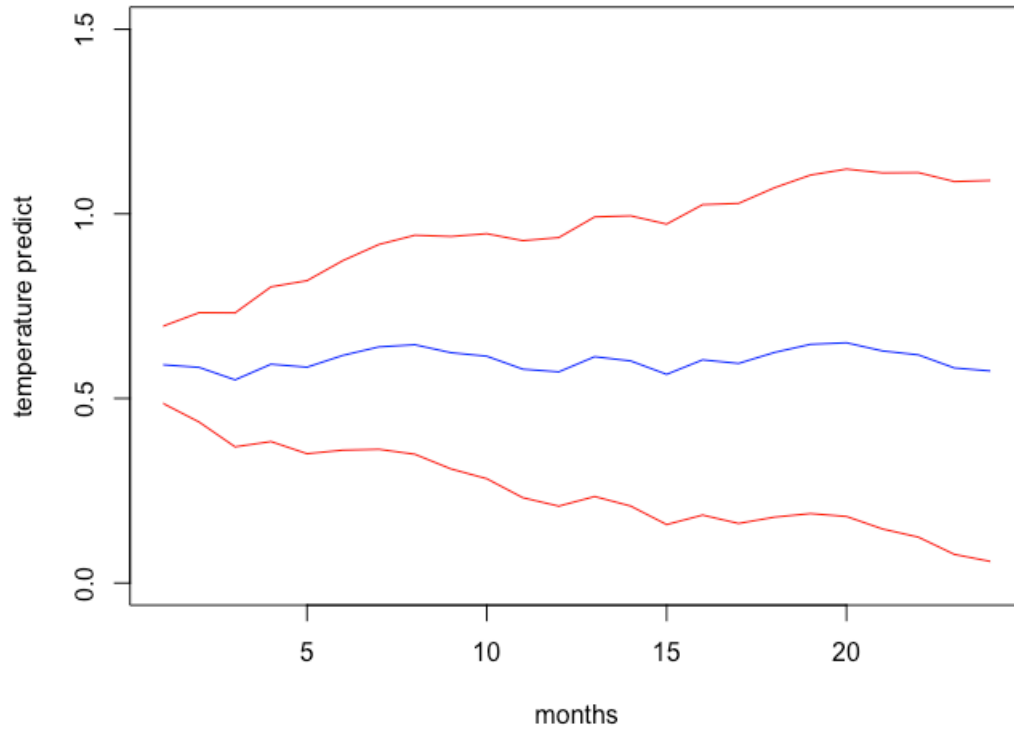


In this plot, we can find the reason that $GARCH(1, 1)$ can't completely wipe out heteroskedasticity, because there is a huge anomaly that can't be explained by an arma on variance.

Forecast

```
fore1 = ugarchforecast(fit1, n.ahead = 24)
fore.diff = as.numeric(fore1@forecast$seriesFor)
fore.sigma = as.numeric(fore1@forecast$sigmaFor)
ts.predict = temp[length(temp)] + cumsum(fore.diff)
ts.predict = ts.predict + myTS.additive$figure
ts.sigma = sqrt(cumsum(fore.sigma^2))
tsup.sigma = ts.predict + ts.sigma
tsdown.sigma = ts.predict - ts.sigma
plot(1:24, ts.predict, ylim=c(0,1.5), type = 'l', col = 'blue',
     xlab = "months", ylab = "temperature predict")
lines(1:24, tsup.sigma, type = 'l', col = 'red')
lines(1:24, tsdown.sigma, type = 'l', col = 'red')
```

Figure 11: forecast



Conclusion: 'sGARCH' have improved the model in the intuitive sense and to some extent fix the heterodasticity.