

# 第八章. 模型诊断

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<http://homepage.zjut.edu.cn/yjq/>

对于一组给定的时间序列  $X_1, X_2, \dots, X_n$ , 经过适当的变换或者差分之后, 转化为平稳的时间序列, 记为  $Y_1, Y_2, \dots, Y_n$ , 利用样本acf、pacf、eacf、ARMA最优子集等进行模型识别定阶。例如AR(2)模型

$$Y_t - \mu = \phi_1(Y_{t-1} - \mu) + \phi_2(Y_{t-2} - \mu) + e_t, \quad \text{其中 } e_t \sim WN(0, \sigma_e^2).$$

并利用极大似然 (或者最小二乘, 矩估计) 有效地估计模型的参数,  $\hat{\mu}, \hat{\phi}_1, \hat{\phi}_2$ , 相应的残差定义为

$$\hat{e}_t = Y_t - (1 - \hat{\phi}_1 - \hat{\phi}_2)\hat{\mu} - \hat{\phi}_1 Y_{t-1} - \hat{\phi}_2 Y_{t-2}$$

类比于回归模型  $Y_t = f(\cdot) + e_t$ , 残差=实际观测值-模型预测值

- $e_t$  不可观测, 残差可以;
- 残差为  $e_t$  的估计值;
- 如果模型被正确识别, 那么残差应该近似具有白噪声的性质。

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## 残差分析

- 绘制残差图: `plot(rstandard(arima(data,order=c(p,d,q))),type= 'b' )`

- 残差的正态性: `hist()`; `qqnorm()`; `qqline()`; `shapiro.test()` ##H\_0:正态

## 案例分析

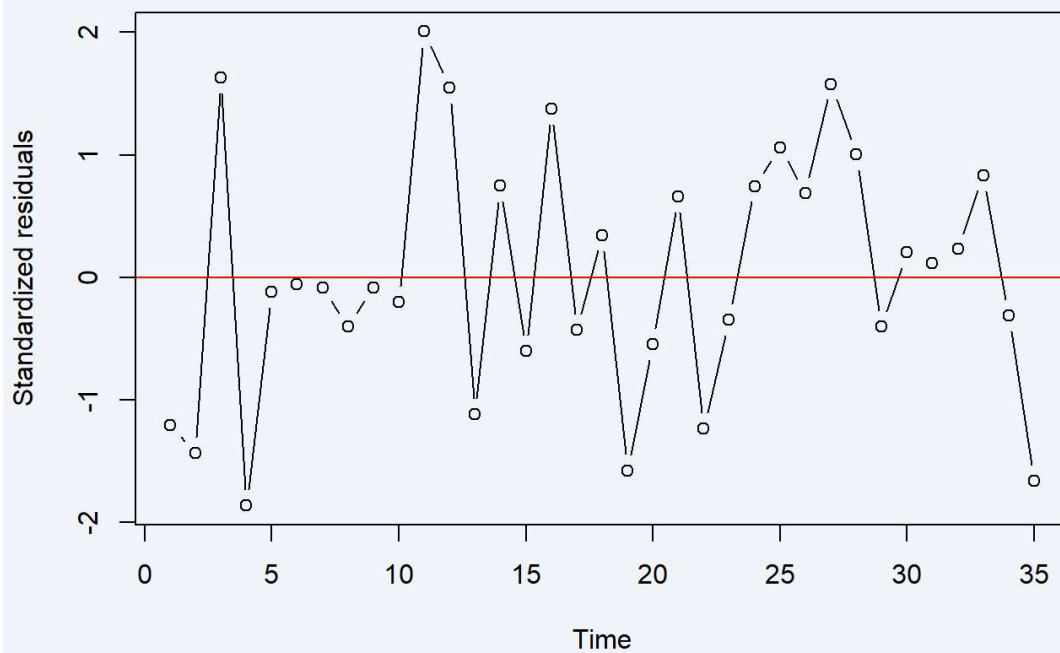
### 化工颜色属性序列

```
> library(TSA)
> data(color)
> m1.color=arima(color,order=c(1,0,0)) ##AR(1)
> m1.color

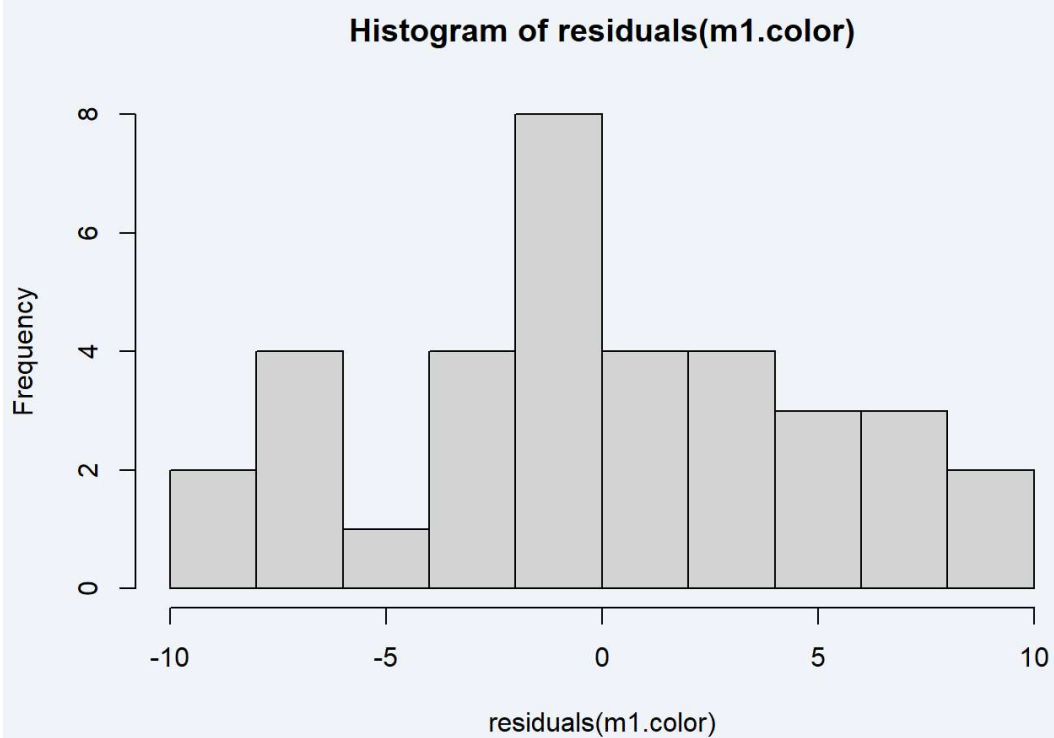
Call:
arima(x = color, order = c(1, 0, 0))

Coefficients:
      ar1  intercept 
  0.5705    74.3293 
s.e.  0.1435    1.9151 

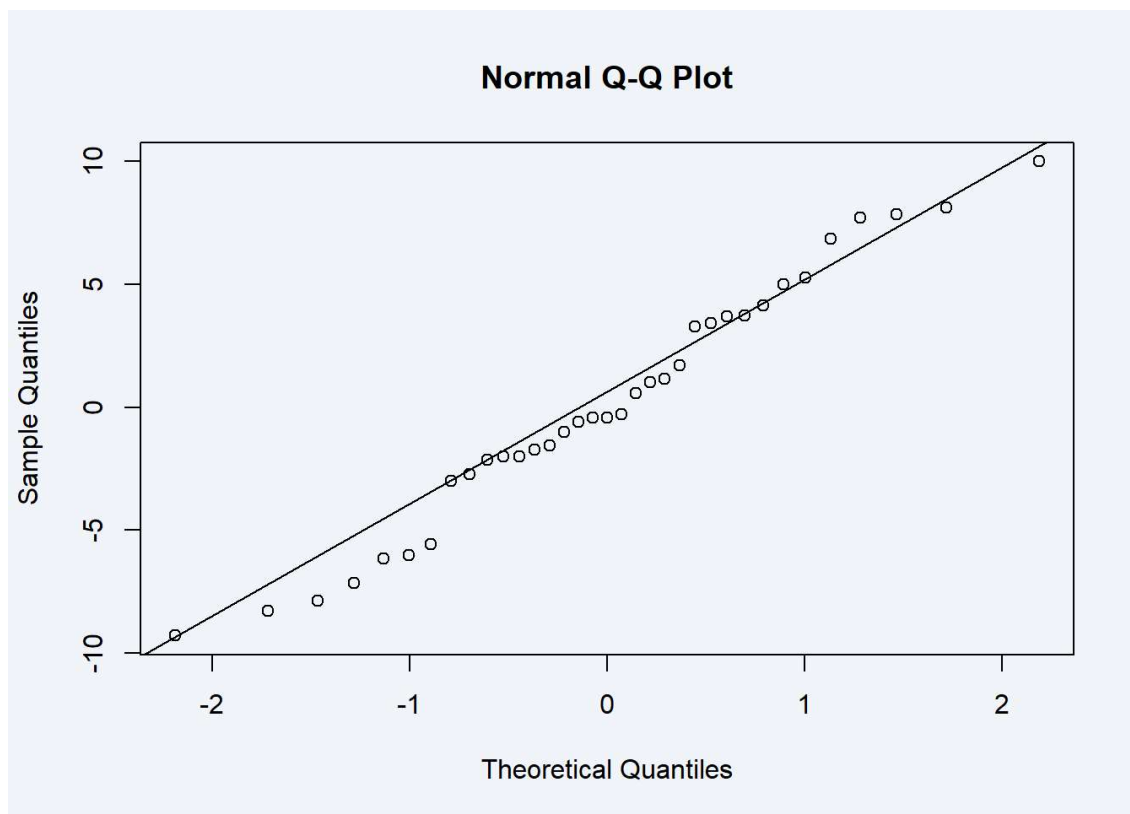
sigma^2 estimated as 24.83:  log likelihood = -106.07,  aic = 216.15
> 
> plot(rstandard(m1.color),ylab='Standardized residuals',type='b')
Error : The fig.showtext code chunk option must be TRUE
> abline(h=0,col='red')
```



```
>
> ###残差正态性检验
> hist(residuals(m1.color))
Error : The fig.showtext code chunk option must be TRUE
```



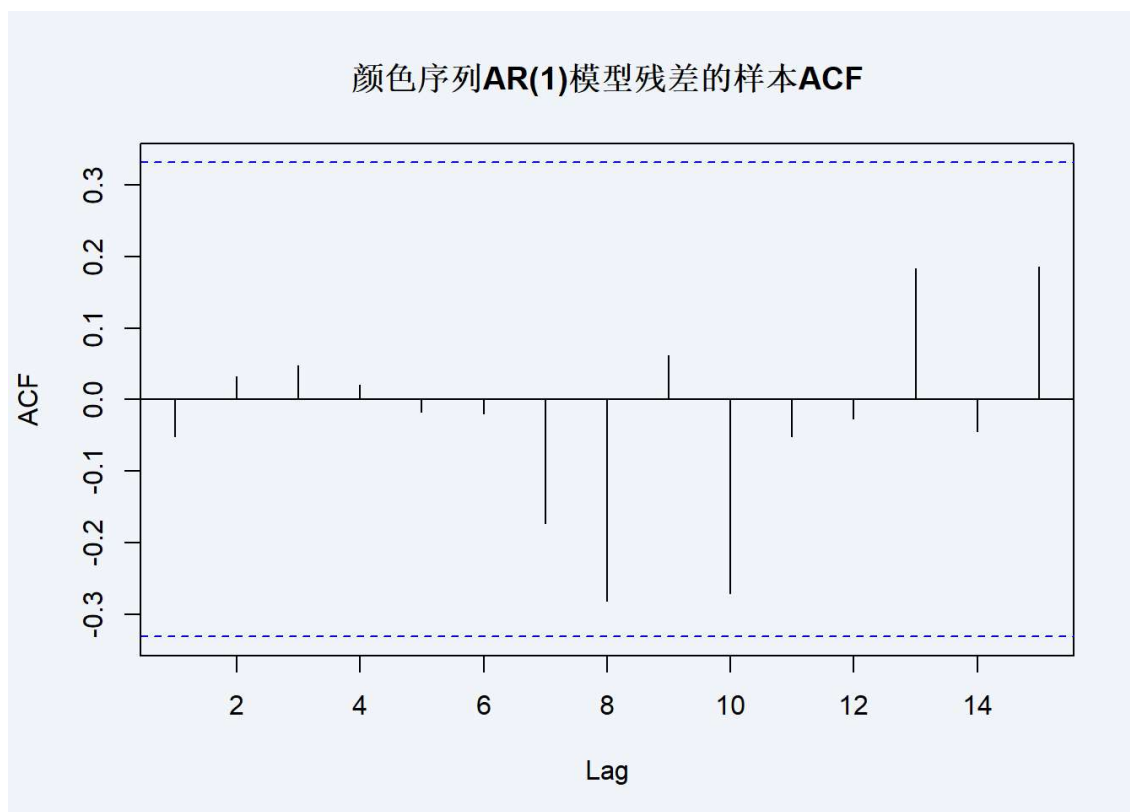
```
> qqnorm(residuals(m1.color))
Error : The fig.showtext code chunk option must be TRUE
> qqline(residuals(m1.color))
```



```
> shapiro.test(residuals(ml.color)) #Shapiro-Wilk检验：正态性

Shapiro-Wilk normality test

data:  residuals(ml.color)
W = 0.97536, p-value = 0.6057
>
> ###残差相关性检验
> acf(residuals(ml.color),main='颜色序列AR(1)模型残差的样本ACF')
Error : The fig.showtext code chunk option must be TRUE
```



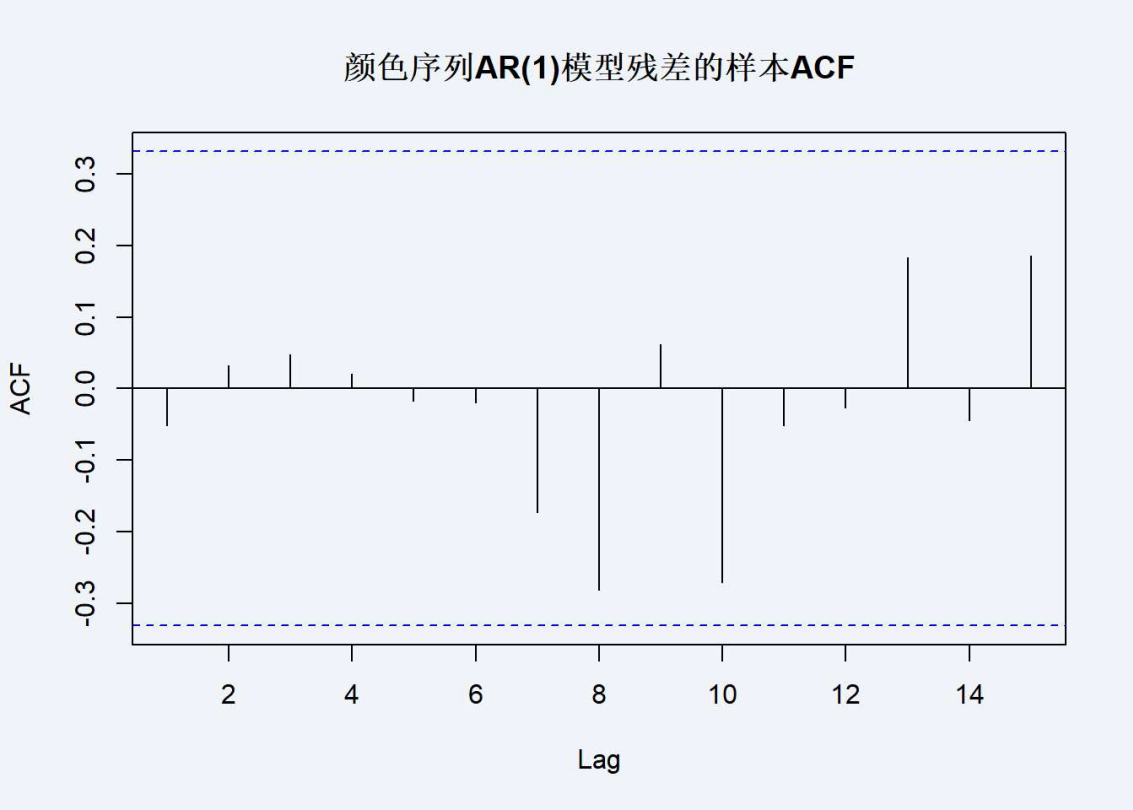
```
> HatPhi<-ml.color$coef[1]; HatPhi
ar1
0.5705478
> n<-ml.color$nobs; n
[1] 35
```

化工颜色属性时间序列拟合的AR(1)模型中,  $\hat{\phi} = 0.5705478$ ,  $n = 35$ , 残差项ACF值的近似标准差为

表8-3 颜色序列AR(1)模型残差的自相关函数的估计及标准差

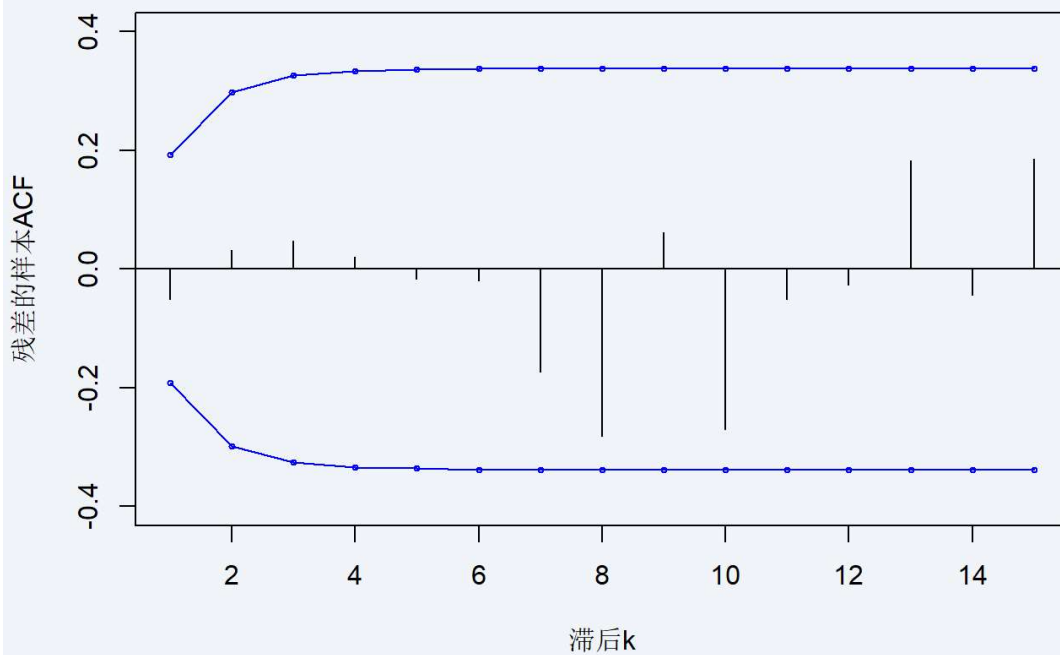
| 滞后k                               | 1      | 2     | 3     | 4     | 5      | 6      |
|-----------------------------------|--------|-------|-------|-------|--------|--------|
| 残差ACF                             | -0.051 | 0.032 | 0.047 | 0.021 | -0.017 | -0.019 |
| $\sqrt{\widehat{Var}(\hat{r}_k)}$ | 0.096  | 0.149 | 0.163 | 0.167 | 0.168  | 0.169  |

```
> HatAcf<-signif(acf(residuals(ml.color),main='颜色序列AR(1)模型残差的样本ACF')$acf,3)
Error : The fig.showtext code chunk option must be TRUE
```



```
> plot(HatAcf,type='h', main='AR(1)模型残差的样本ACF', xlim=c(1,15),ylim=c(-0.4,0.4),xlab='滞后k', ylab='残差的样本ACF')
Error : The fig.showtext code chunk option must be TRUE
> abline(h=0)
> k=1:15
> bd<-c(std,rep(0.169,9))
> par(new=TRUE)
> plot(x=k, y=-2*bd, type='o', cex=0.5, col='blue', xlim=c(1,15), ylim=c(-0.4,0.4), axes=FALSE, xlab='', ylab='')
Error : The fig.showtext code chunk option must be TRUE
> par(new=TRUE)
> plot(x=k, y=2*bd, type='o', cex=0.5, col='blue', xlim=c(1,15), ylim=c(-0.4,0.4), axes=FALSE, xlab='', ylab='')
Error : The fig.showtext code chunk option must be TRUE
```

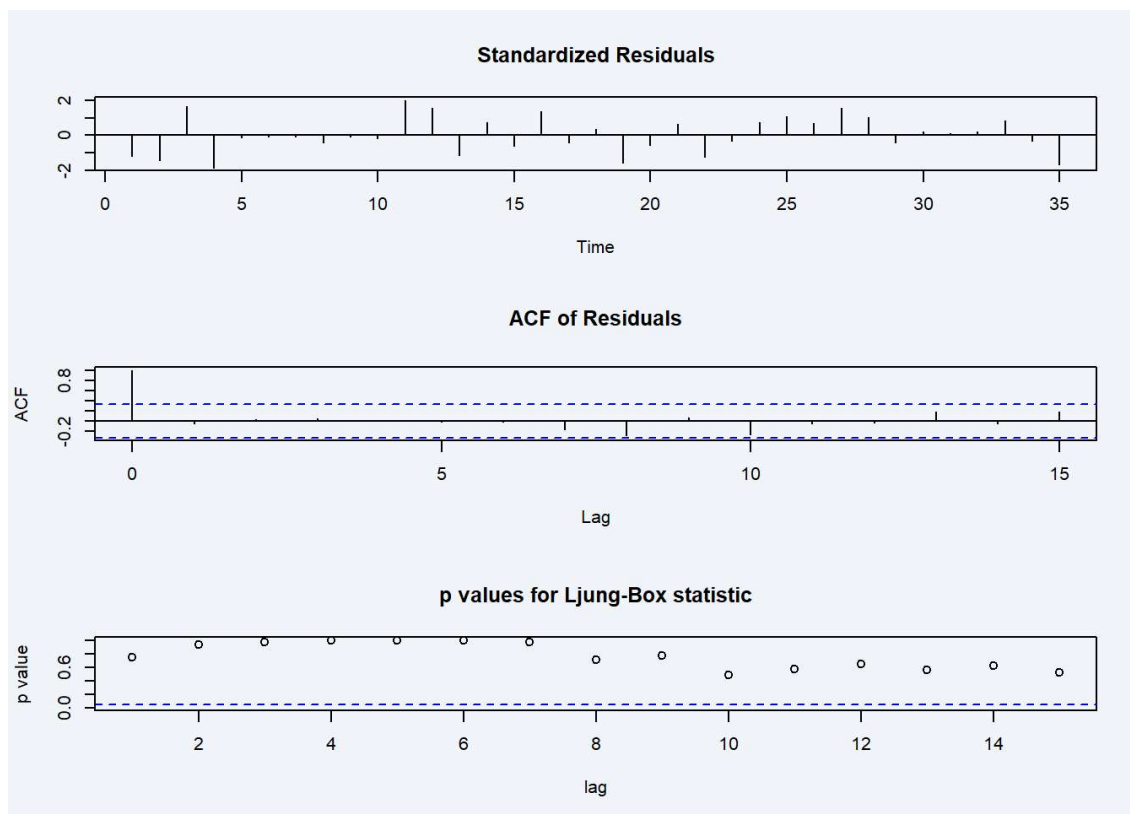
AR(1)模型残差的样本ACF



```
>
> ###残差相关性检验
> HatAcf<-signif(acf(residuals(ml.color),plot=F)$acf[1:6],2);HatAcf # Exhibit 8.11
[1] -0.051  0.032  0.047  0.021 -0.017 -0.019
> # to display the first 6 acf to 2 significant digits.
>
> #Ljung-Box检验 H_0: r_1=r_2=...=r_lag=0, 不相关
> LB.test(ml.color, lag=6) #LB-test the residuals of ml.color

Box-Ljung test

data: residuals from ml.color
X-squared = 0.28032, df = 5, p-value = 0.998
> #LB.test(model, lag = 12, type = c("Ljung-Box", "Box-Pierce"))
>
> tsdiag(ml.color,gof=15,omit.initial=F) # Exhibit 8.12
Error : The fig.showtext code chunk option must be TRUE
Error : The fig.showtext code chunk option must be TRUE
Error : The fig.showtext code chunk option must be TRUE
```



```
> # the tsdiag function is modified from that in the stats package of R.
>
> #runs(residuals(ml.color)) ##游程检验 H_0: 独立性
> #runs(rstandard(ml.color)) ##非参数检验，标准化没有影响
```

## 加拿大野兔丰度序列

```
> library(TSA)
> data(hare)
> ml.hare=arima(sqrt(hare),order=c(3,0,0))
> ml.hare
```

```
Call:
arima(x = sqrt(hare), order = c(3, 0, 0))
```

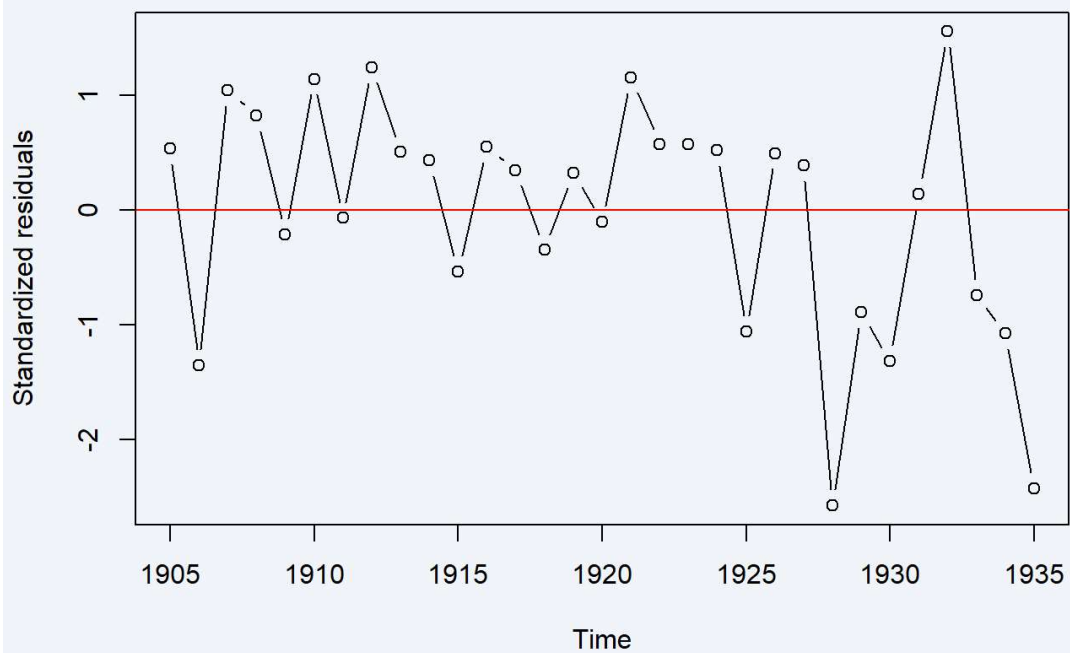
```
Coefficients:
      ar1      ar2      ar3  intercept
    1.0519 -0.2292 -0.3931     5.6923
s.e.    0.1877  0.2942  0.1915     0.3371
```

```
sigma^2 estimated as 1.066:  log likelihood = -46.54,  aic = 101.08
> m2.hare=arima(sqrt(hare),order=c(3,0,0),fixed=c(NA,0,NA,NA))
> m2.hare
```

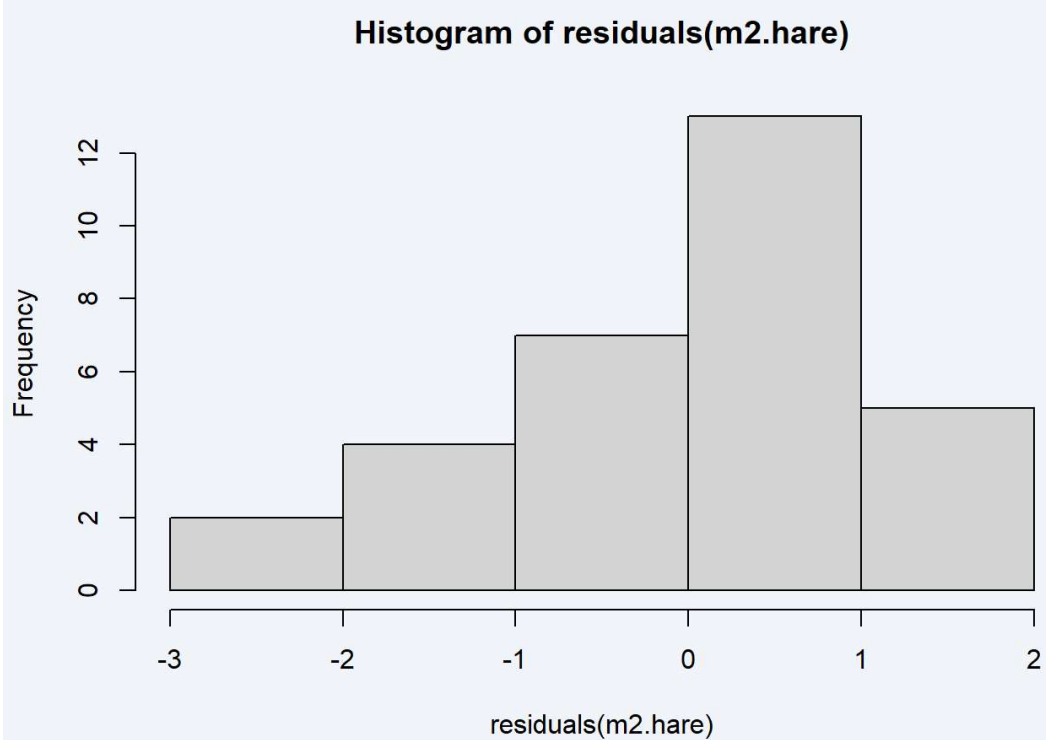
```
Call:
arima(x = sqrt(hare), order = c(3, 0, 0), fixed = c(NA, 0, NA, NA))
```

```
Coefficients:
      ar1  ar2      ar3  intercept
    0.9190   0 -0.5313     5.6889
s.e.    0.0791   0  0.0697     0.3179
```

```
sigma^2 estimated as 1.088:  log likelihood = -46.85,  aic = 99.69
>
> plot(rstandard(m2.hare),ylab='Standardized residuals',type='b')
Error : The fig.showtext code chunk option must be TRUE
> abline(h=0,col='red')
```

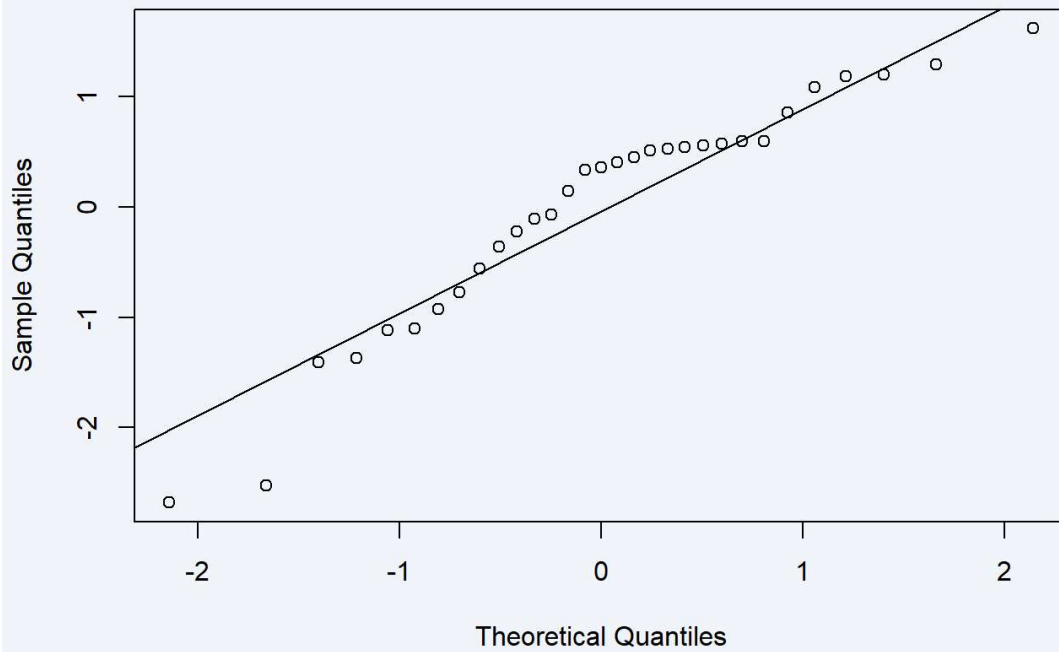


```
>
> ###残差的正态性检验
> hist(residuals(m2.hare))
Error : The fig.showtext code chunk option must be TRUE
```



```
> qqnorm(residuals(m2.hare))
Error : The fig.showtext code chunk option must be TRUE
> qqline(residuals(m2.hare))
```

Normal Q-Q Plot



```
> shapiro.test(residuals(m2.hare)) ##H_0:正态性
```

Shapiro-Wilk normality test

```
data: residuals(m2.hare)
```

```
W = 0.92523, p-value = 0.03257
```

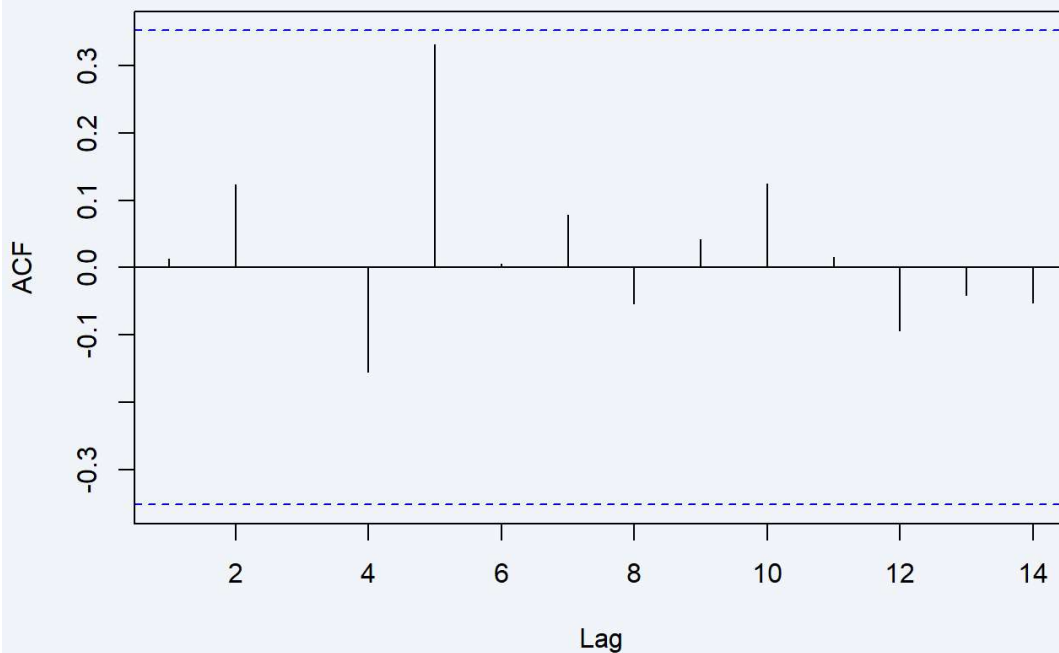
```
>
```

```
> ###残差的相关性检验
```

```
> acf(residuals(m1.hare),main='野兔丰度AR(3)模型残差的样本ACF')
```

```
Error : The fig.showtext code chunk option must be TRUE
```

野兔丰度AR(3)模型残差的样本ACF

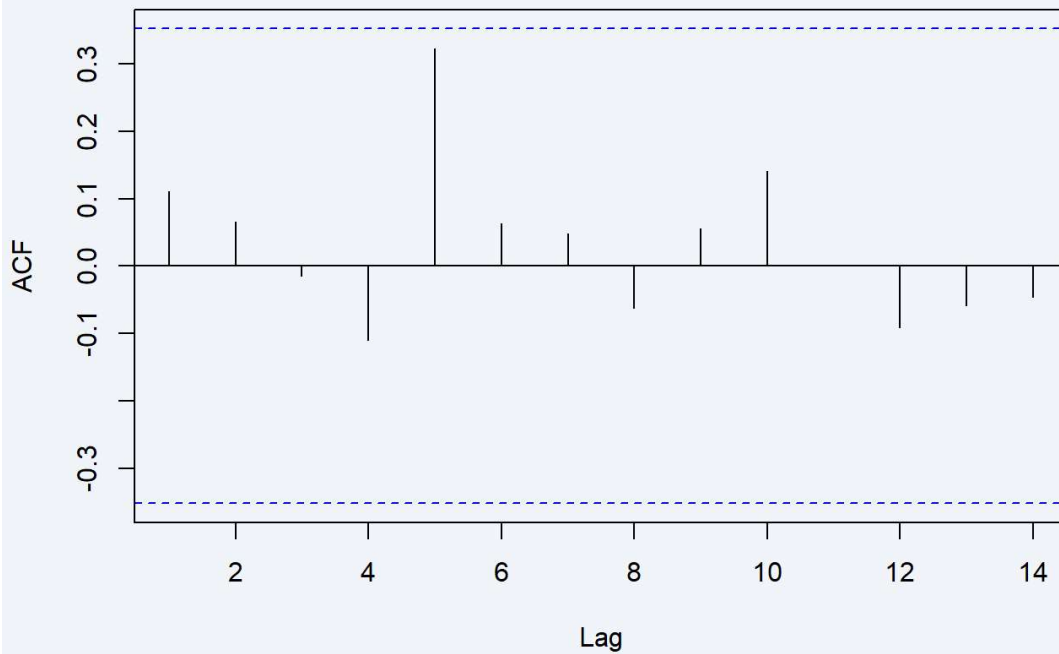


```
> acf(residuals(m2.hare),main='野兔丰度AR(3)/Y_{t-2}模型残差的样本ACF')
```

```
Error : The fig.showtext code chunk option must be TRUE
```



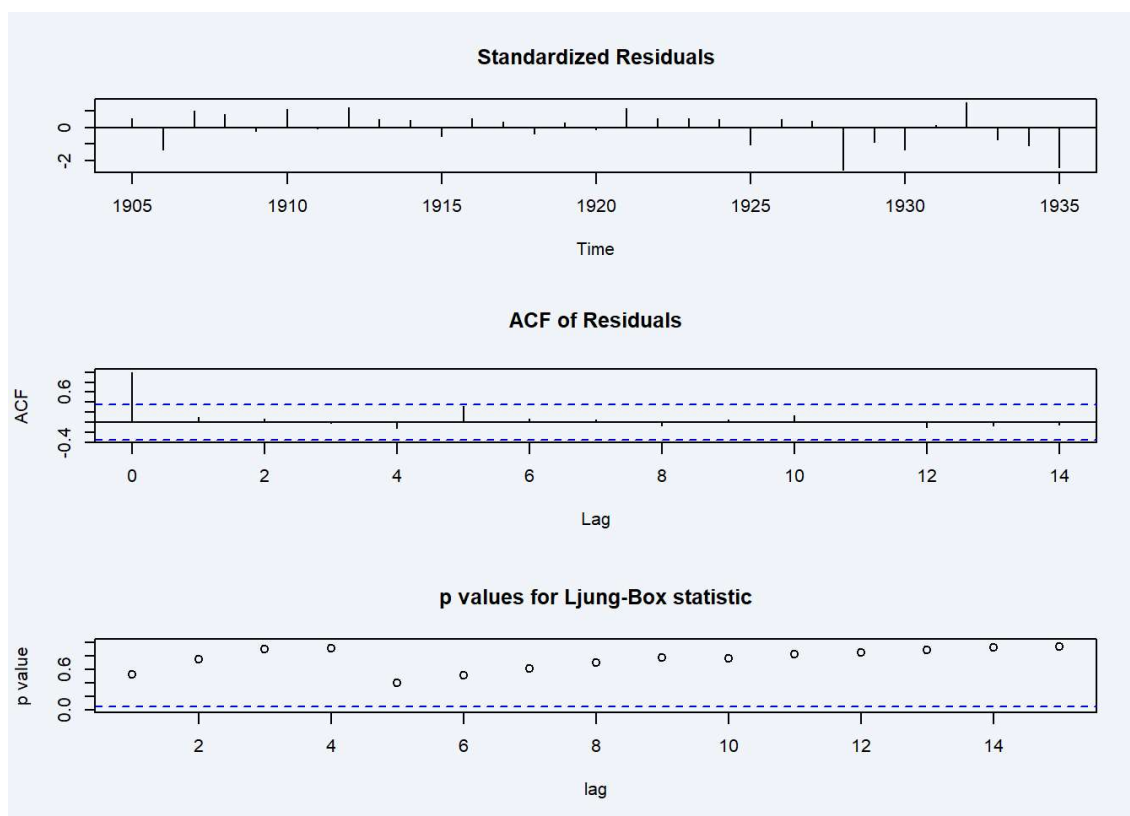
## 野兔丰度AR(3)/Y\_{t-2}模型残差的样本ACF



```
>
> HatAcf<-signif(acf(residuals(m2.hare),plot=F)$acf[1:6],2);HatAcf
[1] 0.110 0.065 -0.014 -0.110 0.320 0.063
> # to display the first 6 acf to 2 significant digits.
>
> #Ljung-Box检验 H_0: r_1=r_2=...=r_lag=0, 不相关
> LB.test(m2.hare, lag=6) #LB-test the residuals of m1.color

Box-Ljung test

data: residuals from m2.hare
X-squared = 5.2802, df = 4, p-value = 0.2597
> #LB.test(model, lag = 12, type = c("Ljung-Box", "Box-Pierce"))
>
> tsdiag(m2.hare,gof=15,omit.initial=F) # Exhibit 8.12
Error : The fig.showtext code chunk option must be TRUE
Error : The fig.showtext code chunk option must be TRUE
Error : The fig.showtext code chunk option must be TRUE
```



```
> # the tsdiag function is modified from that in the stats package of R.
>
> runs(residuals(m2.hare)) ##游程检验 H_0: 独立性
$pvalue
[1] 0.602

$observed.runs
[1] 18

$expected.runs
[1] 16.09677

$n1
[1] 13

$n2
[1] 18

$k
[1] 0
> #runs(rstandard(m2.hare)) ##非参数检验, 标准化没有影响
```

对原始数据进行开方, 然后以AR(3)模型进行拟合, 即

$$\sqrt{Y_t} - \mu = \phi_1(\sqrt{Y_{t-1}} - \mu) + \phi_2(\sqrt{Y_{t-2}} - \mu) + \phi_3(\sqrt{Y_{t-3}} - \mu) + e_t$$

参数的极大似然估计为  $\tilde{\mu} = 5.6923$ ,  $\tilde{\phi}_1 = 1.0519$ ,  $\tilde{\phi}_2 = -0.2292$ ,  $\tilde{\phi}_3 = -0.3930$ , 代入AR(3)模型, 整理得

$$\sqrt{Y_t} = 3.2463 + 1.0519\sqrt{Y_{t-1}} - 0.2292\sqrt{Y_{t-2}} - 0.3930\sqrt{Y_{t-3}} + e_t$$

$\phi_2$ 的95%置信区间为  $[-0.2292 - 2 * 0.2942]$ , 不显著不为零, 故可以去掉该项。令  $\phi_2 = 0$ , 参数的极大似然估计为  $\tilde{\mu} = 5.6889$ ,  $\tilde{\phi}_1 = 0.9190$ ,  $\tilde{\phi}_3 = -0.5313$ , 代入AR(3)模型, 整理得

$$\sqrt{Y_t} = 3.4833 + 0.9190\sqrt{Y_{t-1}} - 0.5313\sqrt{Y_{t-3}} + e_t$$

```
> m3.hare<-arima(sqrt(hare),order=c(2,0,0))
> m3.hare
```

```
Call:
arima(x = sqrt(hare), order = c(2, 0, 0))
```

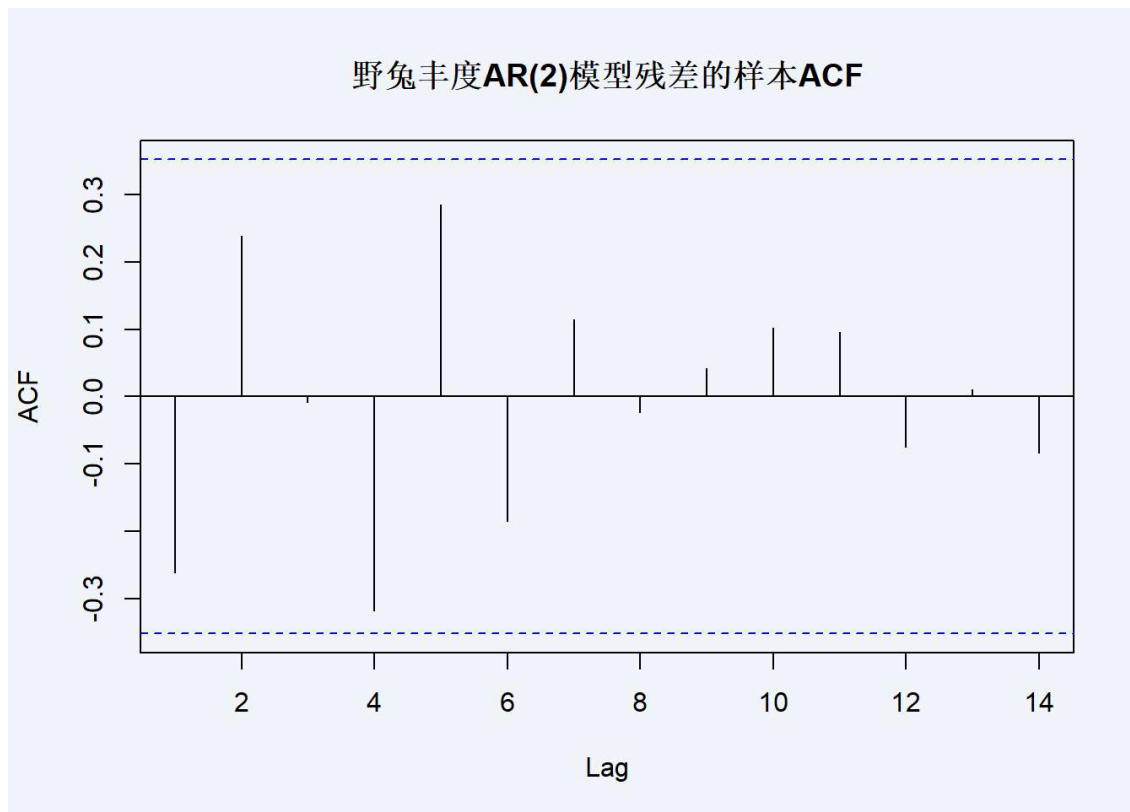
```
Coefficients:
      ar1      ar2  intercept
1.3514 -0.7763      5.7134
```

s.e. 0.1286 0.1242 0.4753

sigma<sup>2</sup> estimated as 1.223: log likelihood = -48.46, aic = 102.91

```
> HatAcf<-acf(residuals(m3.hare),main='野兔丰度AR(2)模型残差的样本ACF')$acf
```

Error : The fig.showtext code chunk option must be TRUE



```
> HatAcf<-round(HatAcf, 4)
```

```
>
```

```
> plot(HatAcf,type='h', main='AR(2)模型残差的样本ACF', xlim=c(1,15),ylim=c(-0.4,0.4),xlab='滞后k', ylab='残差的样本ACF')
```

Error : The fig.showtext code chunk option must be TRUE

```
> abline(h=0)
```

```
>
```

```
> HatPhi_1<-m3.hare$coef[1]; HatPhi_1
```

ar1

1.351401

```
> HatPhi_2<-m3.hare$coef[2]; HatPhi_2
```

ar2

-0.7762724

```
> n<-m3.hare$nobs; n
```

[1] 31

```
> std1<-round(abs(HatPhi_2)/sqrt(n),4); std1 ##\hat(sd (\hat r_1))
```

ar2

0.1394

```
> std2<-round(sqrt(HatPhi_2^2+HatPhi_1^2*(1+HatPhi_2)^2)/sqrt(n),4); std2 ##\hat(sd (\hat r_2))
```

ar2

0.1496

```
> k=1:15
```

```
> bd<-c(std1,std2,rep(round(1/sqrt(n),4),13));bd
```

ar2 ar2

0.1394 0.1496 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796 0.1796

0.1796 0.1796 0.1796 0.1796

```
> par(new=TRUE)
```

```
> plot(x=k, y=-2*bd, type='o', cex=0.5, col='blue', xlim=c(1,15), ylim=c(-0.4,0.4), axes=FALSE, xlab='', ylab='')
```

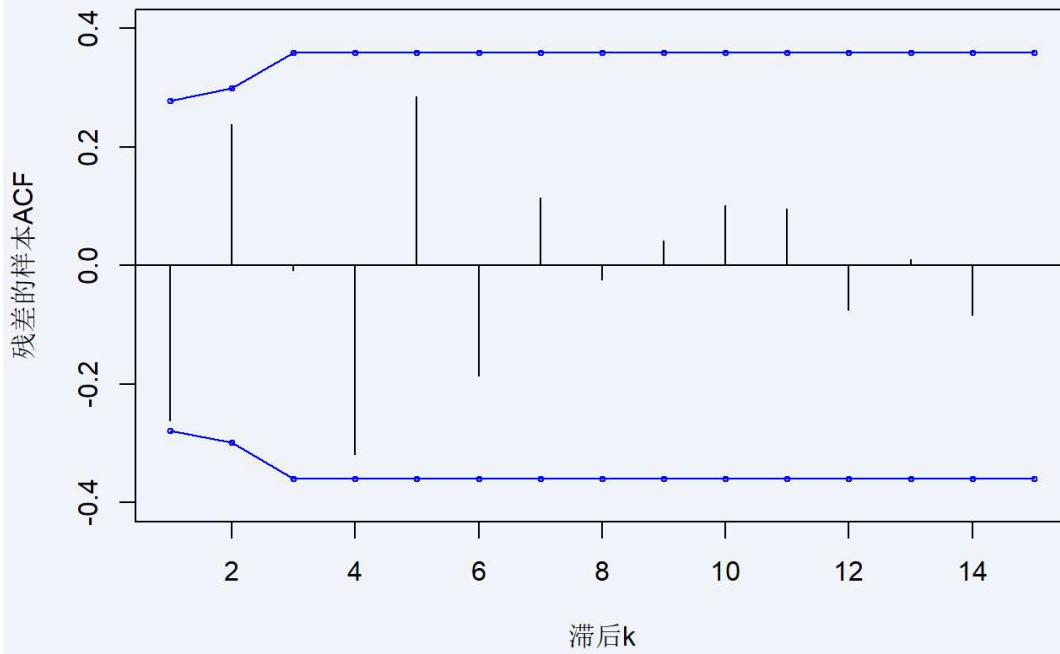
Error : The fig.showtext code chunk option must be TRUE

```
> par(new=TRUE)
```

```
> plot(x=k, y=2*bd, type='o', cex=0.5, col='blue', xlim=c(1,15), ylim=c(-0.4,0.4), axes=FALSE, xlab='', ylab='')
```

Error : The fig.showtext code chunk option must be TRUE

### AR(2)模型残差的样本ACF



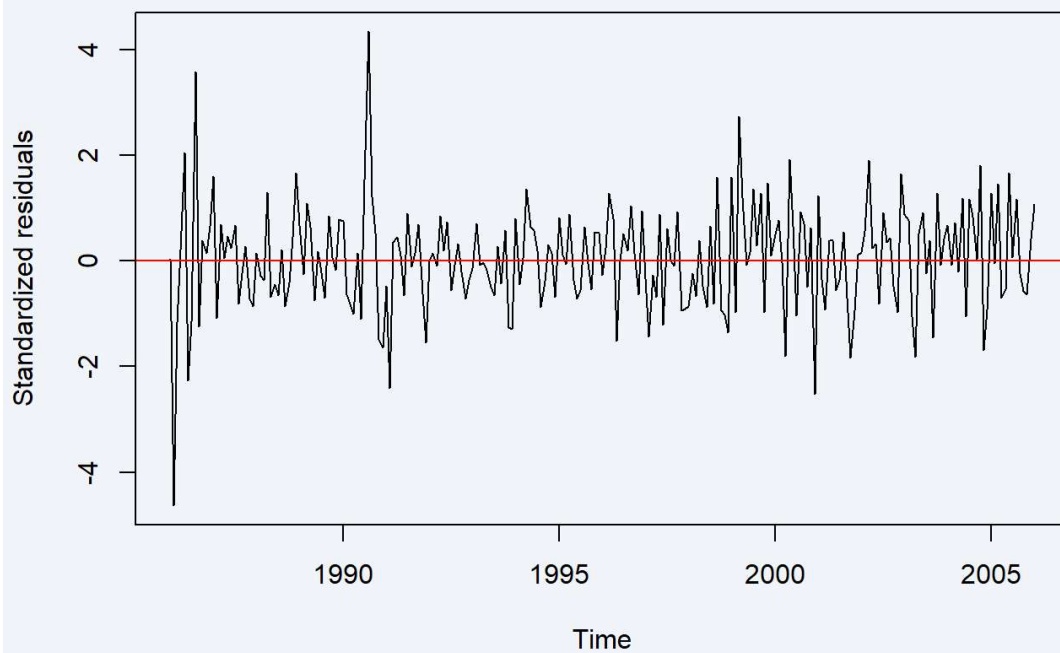
### 石油价格序列

```
> library(TSA)
> data(oil.price)
> m1.oil=arima(log(oil.price),order=c(0,1,1)) ###IMA (1,1)
> m1.oil

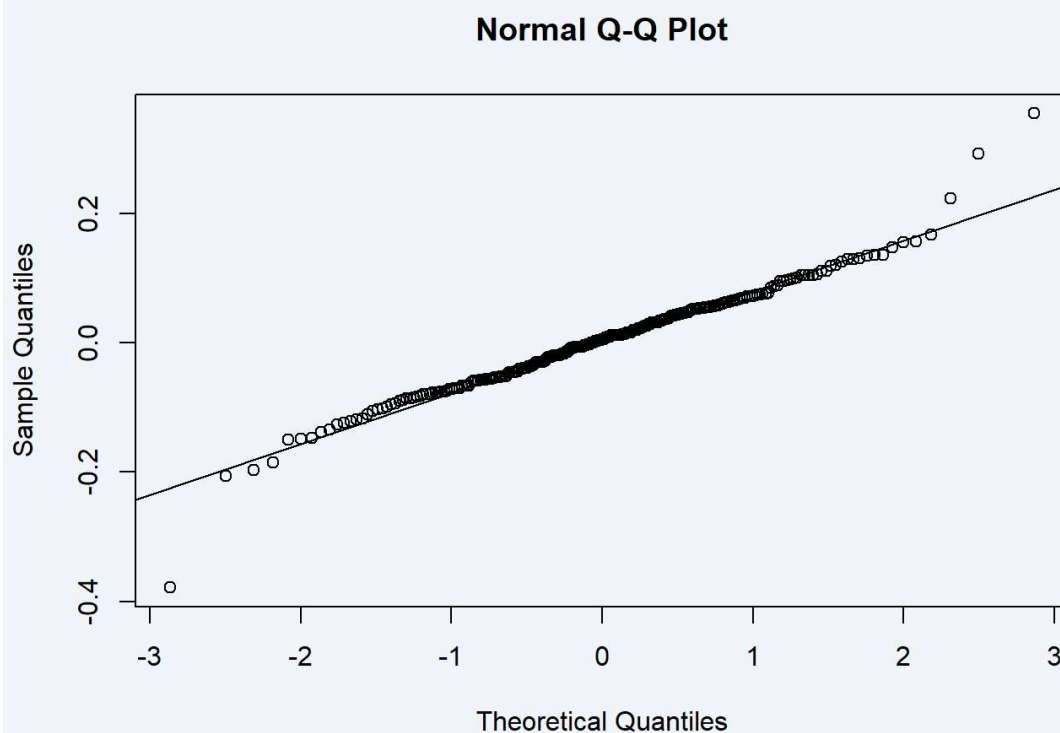
Call:
arima(x = log(oil.price), order = c(0, 1, 1))

Coefficients:
      ma1
    0.2956
s.e.   0.0693

sigma^2 estimated as 0.006689:  log likelihood = 260.29,  aic = -518.58
>
> plot(rstandard(m1.oil),ylab='Standardized residuals',type='l')
Error : The fig.showtext code chunk option must be TRUE
> abline(h=0,col='red')
```



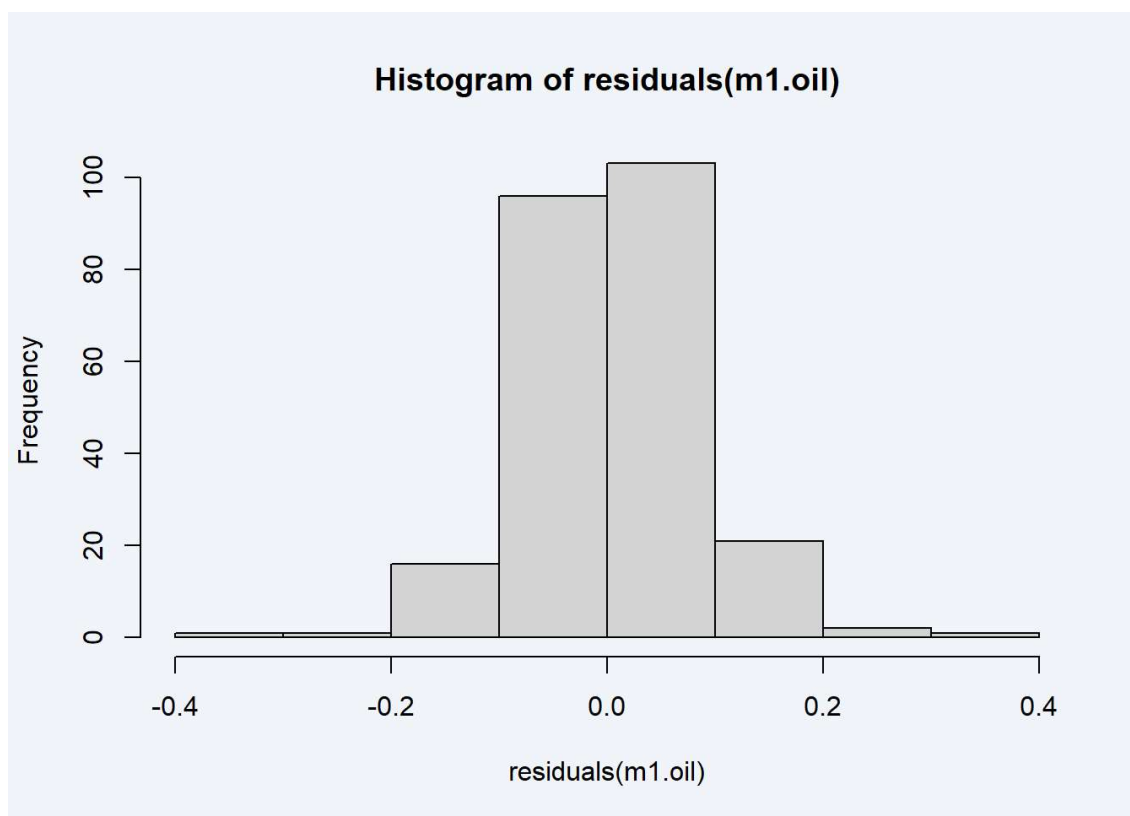
```
>
> ###正态性检验
> qqnorm(residuals(ml.oil))
Error : The fig.showtext code chunk option must be TRUE
> qqline(residuals(ml.oil))
```



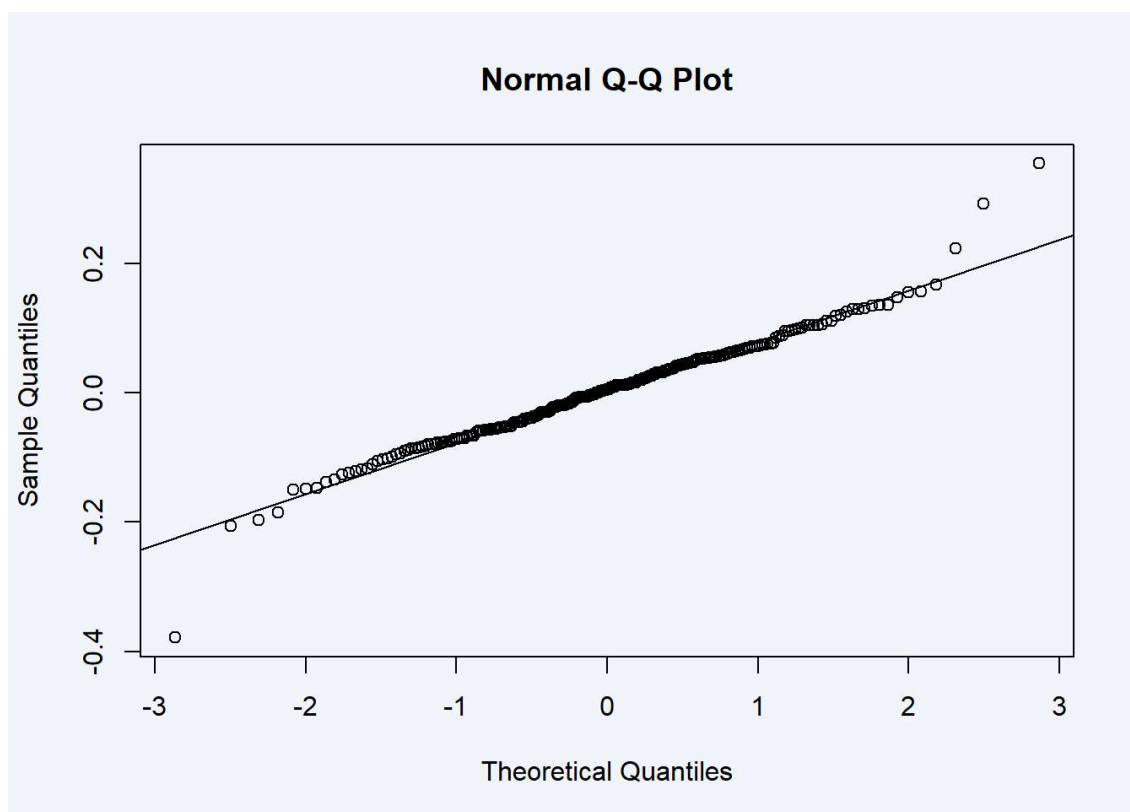
```
> shapiro.test(residuals(ml.oil)) ##H_0:正态性

Shapiro-Wilk normality test

data: residuals(ml.oil)
W = 0.96883, p-value = 3.937e-05
>
> ###残差的正态性检验
> hist(residuals(ml.oil))
Error : The fig.showtext code chunk option must be TRUE
```



```
> qqnorm(residuals(m1.oil))
Error : The fig.showtext code chunk option must be TRUE
> qqline(residuals(m1.oil))
```

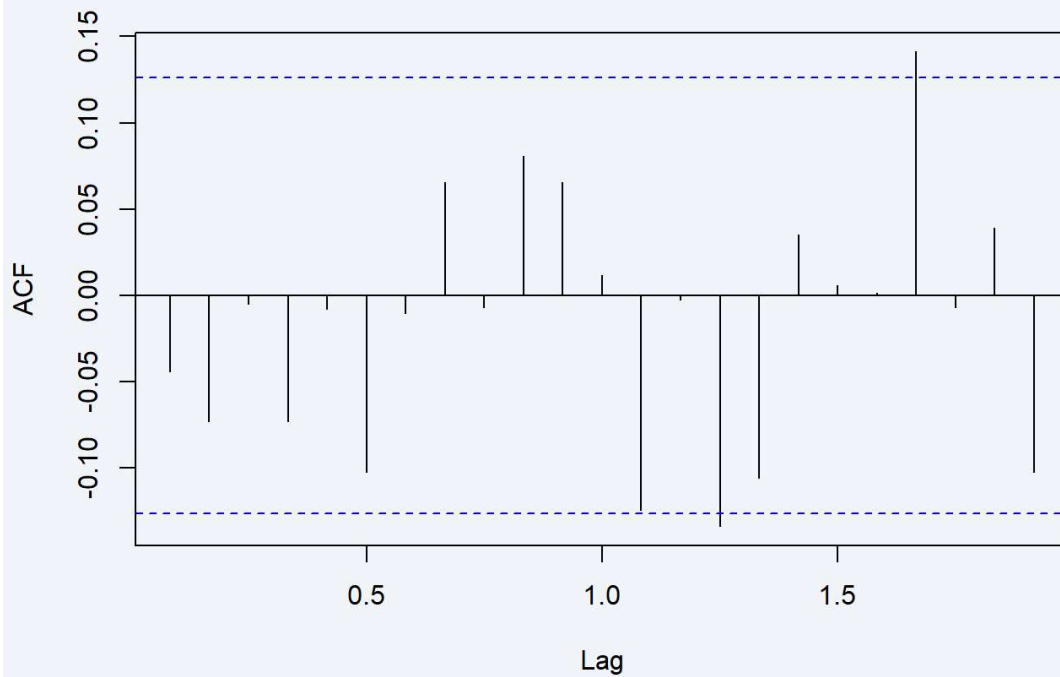


```
> shapiro.test(residuals(m1.oil)) ##H_0: 正态性

      Shapiro-Wilk normality test

data:  residuals(m1.oil)
W = 0.96883, p-value = 3.937e-05
>
> ###残差的相关性检验
> acf(residuals(m1.oil), main='石油价格对数化ARIMA(0,1,1)模型残差的样本ACF')
Error : The fig.showtext code chunk option must be TRUE
```

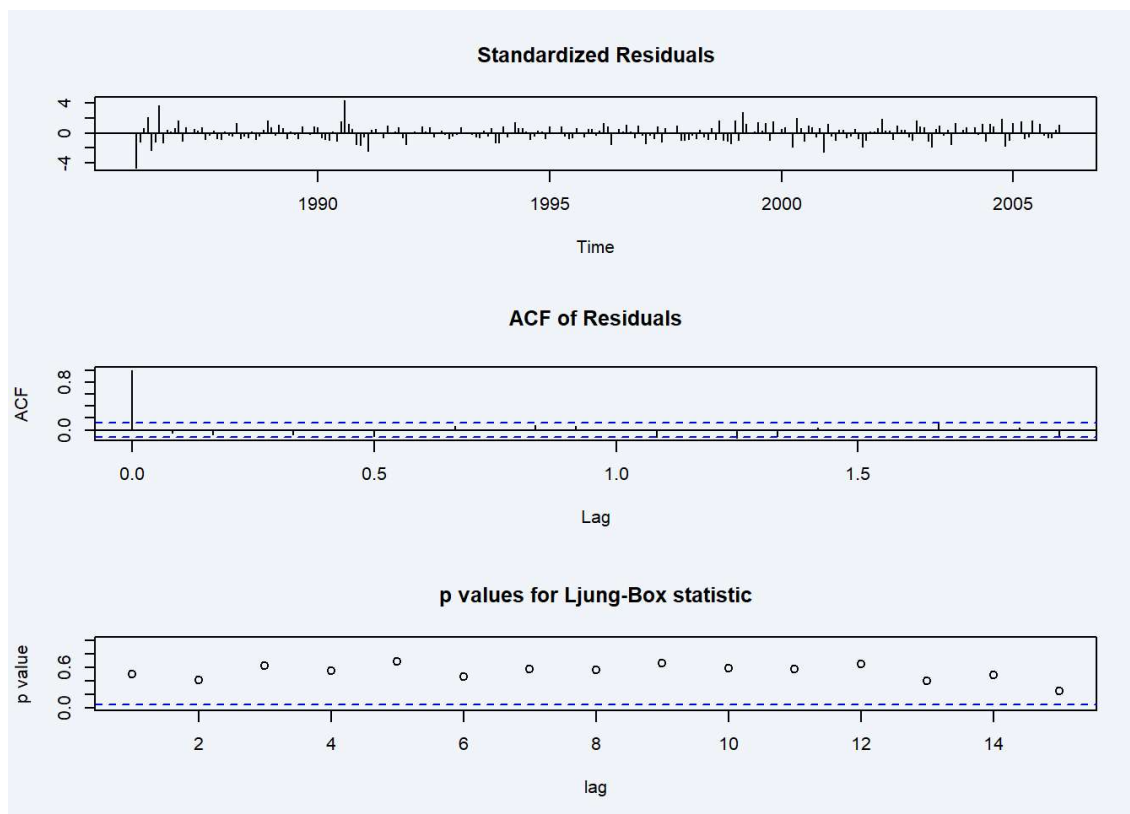
石油价格对数化ARIMA(0,1,1)模型残差的样本ACF



```
>
> HatAcf<-signif(acf(residuals(ml.oil),plot=F)$acf[1:6],2);HatAcf
[1] -0.0440 -0.0730 -0.0050 -0.0730 -0.0078 -0.1000
> # to display the first 6 acf to 2 significant digits.
>
> #Ljung-Box检验 H_0: r_1=r_2=...=r_lag=0, 不相关
> LB.test(ml.oil, lag=6) #LB-test the residuals of ml.oil

Box-Ljung test

data: residuals from ml.oil
X-squared = 5.6847, df = 5, p-value = 0.3381
> #LB.test(model, lag = 12, type = c("Ljung-Box", "Box-Pierce"))
>
> tsdiag(ml.oil,gof=15,omit.initial=F) # Exhibit 8.12
Error : The fig.showtext code chunk option must be TRUE
Error : The fig.showtext code chunk option must be TRUE
Error : The fig.showtext code chunk option must be TRUE
```



```
> # the tsdiag function is modified from that in the stats package of R.
>
> runs(residuals(m1.oil)) ##游程检验 H_0: 独立性
$pvalue
[1] 0.341

$observed.runs
[1] 129

$expected.runs
[1] 121.1494

$n1
[1] 114

$n2
[1] 127

$k
[1] 0
> #runs(rstandard(m2.hare)) ##非参数检验，标准化没有影响
```

对原始数据进行对数变换，然后以IMA(1, 1)模型进行拟合，即

$$\nabla \log Y_t - \mu = e_t - \theta e_{t-1}$$

极大似然估计的结果表明，AIC最小的是零均值的IMA(1, 1)模型。

$$\log Y_t = \log Y_{t-1} + e_t + 0.2956 * e_{t-1}.$$

## 案例分析

- 残差的自相关性：残差的自相关函数记为  $\hat{r}_k$ ，对于较大的  $n$ ，
  - 白噪声的样本自相关函数  $r_k \sim AN(0, \frac{1}{n})$ ,  $Corr(r_k, r_j) \approx 0$ .
  - AR(1)模型残差  $\hat{e}_t = Y_t - \hat{\phi}Y_{t-1}$  的自相关函数



$$\begin{cases} Var(\hat{r}_1) \approx \frac{\phi^2}{n} \\ Var(\hat{r}_k) \approx \frac{1-(1-\phi^2)\phi^{2k-2}}{n}, & k > 1 \\ Corr(\hat{r}_1, \hat{r}_k) \approx -sign(\phi) \frac{(1-\phi^2)\phi^{k-2}}{1-(1-\phi^2)\phi^{2k-2}} \end{cases}$$

图表

表8-1: 标准差

表8-1: AR(1)模型残差自相关函数 $\sqrt{nVar(\hat{r}_k)}$ 的逼近

| $k$ | $\phi = 0.3$ | $\phi = 0.5$ | $\phi = 0.7$ | $\phi = 0.9$ |
|-----|--------------|--------------|--------------|--------------|
| 1   | 0.3          | 0.5          | 0.7          | 0.9          |
| 2   | 0.96         | 0.9          | 0.87         | 0.92         |
| 3   | 1            | 0.98         | 0.94         | 0.94         |
| 4   | 1            | 0.99         | 0.97         | 0.95         |
| 5   | 1            | 1            | 0.99         | 0.96         |
| 6   | 1            | 1            | 0.99         | 0.97         |
| 7   | 1            | 1            | 1            | 0.97         |
| 8   | 1            | 1            | 1            | 0.98         |
| 9   | 1            | 1            | 1            | 0.98         |

表8-2: 相关系数

表8-2: AR(1)模型残差自相关函数 $Corr(\hat{r}_1, \hat{r}_k)$ 的逼近

| $k$ | $\phi = 0.3$ | $\phi = 0.5$ | $\phi = 0.7$ | $\phi = 0.9$ |
|-----|--------------|--------------|--------------|--------------|
| 1   | 1            | 1            | 1            | 1            |
| 2   | -0.99        | -0.92        | -0.68        | -0.22        |
| 3   | -0.28        | -0.39        | -0.41        | -0.2         |
| 4   | -0.08        | -0.19        | -0.27        | -0.17        |
| 5   | -0.02        | -0.09        | -0.18        | -0.15        |
| 6   | -0.01        | -0.05        | -0.12        | -0.13        |
| 7   | 0            | -0.02        | -0.09        | -0.12        |
| 8   | 0            | -0.01        | -0.06        | -0.11        |
| 9   | 0            | -0.01        | -0.04        | -0.09        |

图表

\* AR(2)模型残差  $\hat{e}_t = Y_t - \hat{\phi}_1 Y_{t-1} - \hat{\phi}_2 Y_{t-2}$  的自相关函数

$$\begin{cases} Var(\hat{r}_1) \approx \frac{\phi_2^2}{n} \\ Var(\hat{r}_2) \approx \frac{\phi_2^2 + \phi_1^2(1+\phi_2)^2}{n} \\ Var(\hat{r}_k) \approx \frac{1}{n}, & k \geq 3 \end{cases}$$

# • 自相关检验

残差的自相关函数记为 $r_1, r_2, \dots$ , 自相关检验问题

\* 原假设  $H_0 : r_1 = r_2 = \dots = r_K = 0$

\* 备择假设  $H_1 : \text{至少存在某个 } r_k \neq 0, 1 \leq k \leq K$

\* Box-Pierce检验:

$$Q = n(\hat{r}_1^2 + \hat{r}_2^2 + \cdots + \hat{r}_K^2) \overset{ARMA(p,q)}{\sim}_{appr.} \chi^2_{(K-p-q)}$$

\* Ljung-Box检验:

$$Q_* = n(n+2)\left(\frac{\hat{r}_1^2}{n-1} + \frac{\hat{r}_2^2}{n-2} + \cdots + \frac{\hat{r}_K^2}{n-K}\right) \overset{ARMA(p,q)}{\sim}_{appr.} \chi^2_{(K-p-q)}$$

## 过度拟合和参数冗余

### • 过度拟合

识别并拟合出一个初步合适的模型之后, 在此基础上, 寻找一些更一般的包含初始模型的扩展模型, 然后进行比较, **检查额外的参数是否显著地不为零, 共同的参数估计是否有显著的改变。**

\* 显著性t检验  $H_0 : \beta_j = 0$  vs.  $H_1 : \beta_j \neq 0$

- 统计量  $t_j = \frac{\hat{\beta}_j}{sd(\hat{\beta}_j)} \overset{H_0}{\sim} t(n-m)$ ,  $n$  样本容量,  $m$  参数个数

- 拒绝域  $\{t_j : |t_j| \geq t_{\alpha/2}(n-m)\}$

- p-值  $\Pr(|t_{n-m}| \geq |t_j| | \beta_j = 0)$

### • 参数冗余

考虑下面的ARMA(2,3)模型

$$Y_t - (\phi + c)Y_{t-1} + \phi c Y_{t-2} = e_t - (\theta_1 + c)e_{t-1} - (\theta_2 - c\theta_1)e_{t-2} + c\theta_2 e_{t-3}$$

- AR参数多项式  $1 - (\phi + c)x + \phi c x^2 = (1 - \phi x)(1 - cx)$

- MA参数多项式  $1 - (\theta_1 + c)x - (\theta_2 - c\theta_1)x^2 + c\theta_2 x^3 = (1 - \theta_1 x - \theta_2 x^2)(1 - cx)$

$$(1 - \phi B)(1 - cB)Y_t = (1 - \theta_1 B - \theta_2 B^2)(1 - cB)e_t$$

ARMA(2,3)模型中的参数 $c$ 是可以取任意值的, 是不可识别的。等价于ARMA(1,2)模型

$$Y_t - \phi Y_{t-1} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2}$$

### • 案例分析 (化工颜色属性序列)

| Model     | AIC      | LogLik    | Sig2     | AR_1      | AR_2      | MA_1       | MU       |
|-----------|----------|-----------|----------|-----------|-----------|------------|----------|
| AR(1)     | 216.1471 | -106.0735 | 24.83407 | 0.5705478 | NA        | NA         | 74.32928 |
| AR(2)     | 217.8428 | -105.9214 | 24.59941 | 0.5173004 | 0.1004908 | NA         | 74.15508 |
| ARMA(1,1) | 217.8847 | -105.9423 | 24.63363 | 0.6720801 | NA        | -0.1467323 | 74.17298 |
| ARMA(2,1) | 219.8202 | -105.9101 | 24.57902 | 0.2188729 | 0.2735330 | 0.3036481  | 74.16528 |

Call:  
arima(x = color, order = c(1, 0, 0))

Coefficients:  
ar1 intercept  
0.5705 74.3293  
s.e. 0.1435 1.9151

sigma^2 estimated as 24.83: log likelihood = -106.07, aic = 216.15

Call:

```
arima(x = color, order = c(2, 0, 0))
```

Coefficients:

|      | ar1    | ar2    | intercept |
|------|--------|--------|-----------|
|      | 0.5173 | 0.1005 | 74.1551   |
| s.e. | 0.1717 | 0.1815 | 2.1463    |

sigma^2 estimated as 24.6: log likelihood = -105.92, aic = 217.84

Call:

```
arima(x = color, order = c(1, 0, 1))
```

Coefficients:

|      | ar1    | ma1     | intercept |
|------|--------|---------|-----------|
|      | 0.6721 | -0.1467 | 74.1730   |
| s.e. | 0.2147 | 0.2742  | 2.1357    |

sigma^2 estimated as 24.63: log likelihood = -105.94, aic = 217.88

Call:

```
arima(x = color, order = c(2, 0, 1))
```

Coefficients:

|      | ar1    | ar2    | ma1    | intercept |
|------|--------|--------|--------|-----------|
|      | 0.2189 | 0.2735 | 0.3036 | 74.1653   |
| s.e. | 2.0056 | 1.1376 | 2.0650 | 2.1121    |

sigma^2 estimated as 24.58: log likelihood = -105.91, aic = 219.82

消除掉冗余参数之后，化工颜色属性序列的合适模型为AR(1):

$$Y_t - \mu = \phi(Y_{t-1} - \mu) + e_t$$

- 最小均方误差预测

基于序列可获得的直到时间 $t$ 的历史数据，即 $Y_1, Y_2, \dots, Y_t$ ，预测未来 $m$ 期的值 $Y_{t+m}$ ，称时间 $t$ 为**预测起点**， $m$ 为**预测前置时间**，而用 $\hat{Y}_t(m)$ 代表预测值。最小均方误差预测为

$$\hat{Y}_t(m) = E(Y_{t+m} | Y_1, Y_2, \dots, Y_t)$$

\* 考虑AR(1)模型未来1期预测的问题:

$$Y_{t+1} - \mu = \phi(Y_t - \mu) + e_{t+1}$$

给定 $Y_1, Y_2, \dots, Y_t$ ，取条件期望得

$$\begin{aligned}\hat{Y}_t(1) &= E(\mu | Y_1, \dots, Y_t) + \phi E((Y_t - \mu) | Y_1, \dots, Y_t) + E(e_{t+1} | Y_1, \dots, Y_t) \\ &= \mu + \phi(Y_t - \mu)\end{aligned}$$

\* 考虑AR(1)模型未来2期预测的问题:

$$Y_{t+2} - \mu = \phi(Y_{t+1} - \mu) + e_{t+2}$$

给定 $Y_1, Y_2, \dots, Y_t$ ，取条件期望得

$$\begin{aligned}\hat{Y}_t(2) &= E(\mu | Y_1, \dots, Y_t) + \phi E((Y_{t+1} - \mu) | Y_1, \dots, Y_t) + E(e_{t+2} | Y_1, \dots, Y_t) \\ &= \mu + \phi(\hat{Y}_t(1) - \mu)\end{aligned}$$

\* 考虑AR(1)模型未来 $m$ 期预测的问题:

$$Y_{t+m} - \mu = \phi(Y_{t+(m-1)} - \mu) + e_{t+m}$$

给定  $Y_1, Y_2, \dots, Y_t$ , 取条件期望得

$$\begin{aligned}\hat{Y}_t(m) &= E(\mu|Y_1, \dots, Y_t) + \phi E((Y_{t+(m-1)} - \mu)|Y_1, \dots, Y_t) + E(e_{t+m}|Y_1, \dots, Y_t) \\ &= \mu + \phi (\hat{Y}_t(m-1) - \mu) = \mu + \phi [\mu + \phi (\hat{Y}_t(m-2) - \mu)] \\ &= \mu + \phi^2 (\hat{Y}_t(m-2) - \mu) = \dots \\ &= \mu + \phi^m (Y_t - \mu)\end{aligned}$$

```
> ml.color
```

Call:

```
arima(x = color, order = c(1, 0, 0))
```

Coefficients:

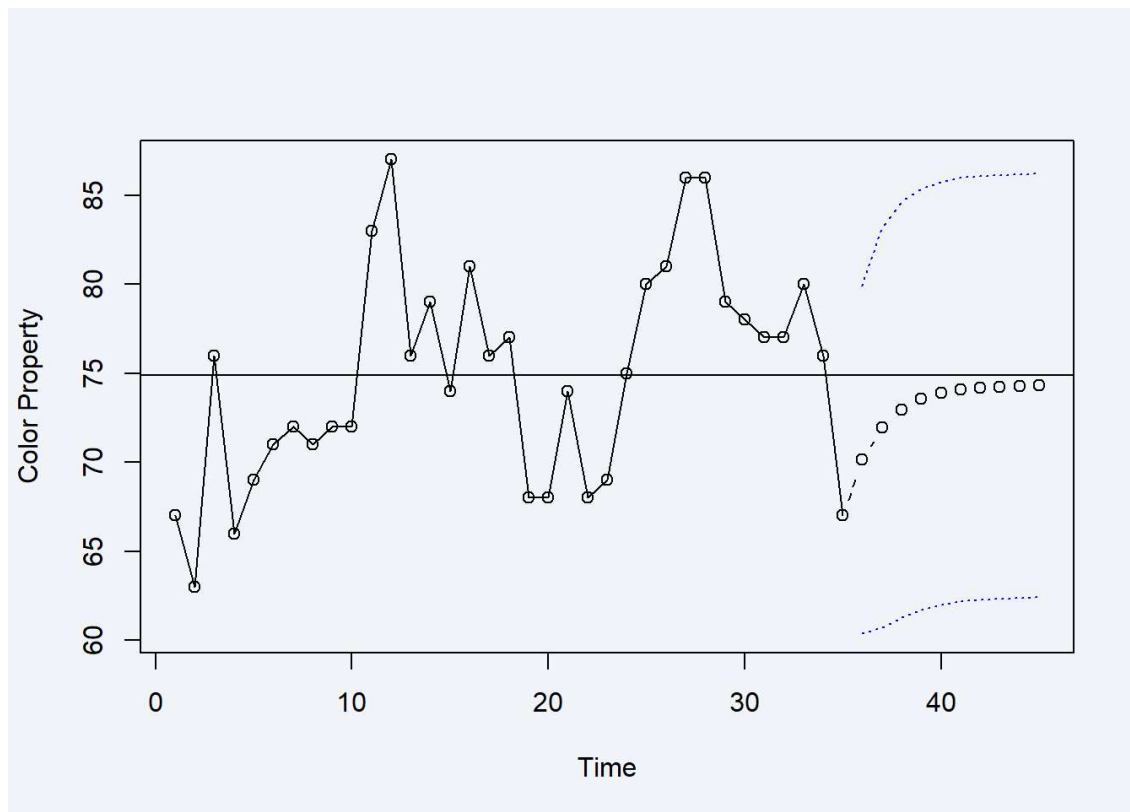
|      | arl    | intercept |
|------|--------|-----------|
|      | 0.5705 | 74.3293   |
| s.e. | 0.1435 | 1.9151    |

sigma^2 estimated as 24.83: log likelihood = -106.07, aic = 216.15

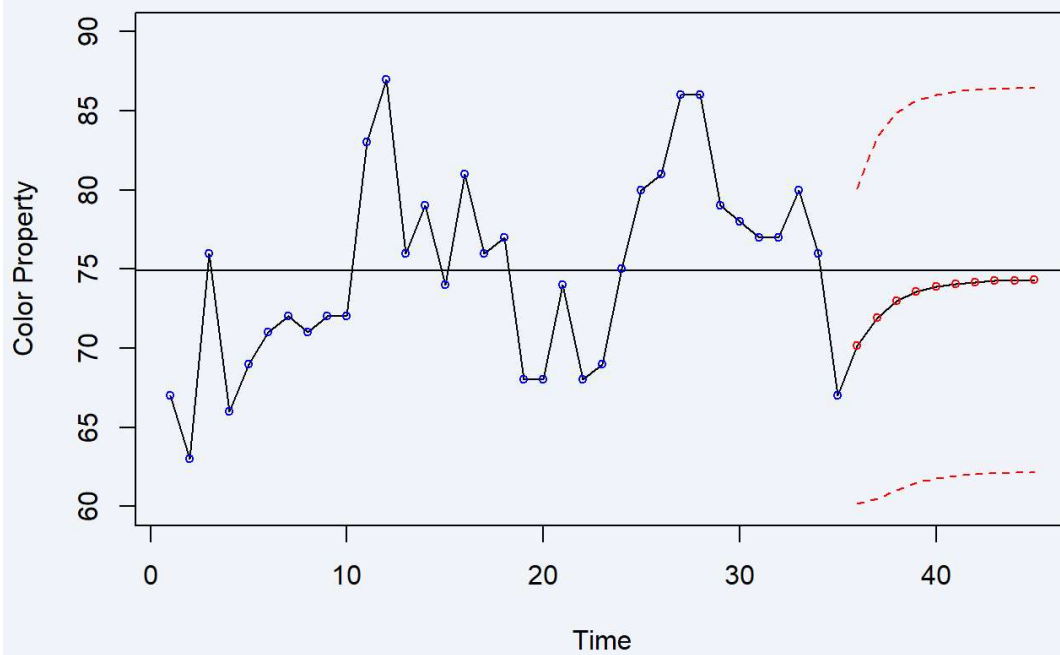
```
> plot(ml.color, n.ahead=10, type='b', xlab='Time', ylab='Color Property', col='blue')
```

Error : The fig.showtext code chunk option must be TRUE

```
> abline(h=mean(color))
```



```
>
> m=10
> pre<-predict(ml.color,n.ahead=m)$pred
> se<-predict(ml.color,n.ahead=m)$se
> lowBd<-pre-2*se
> upBd<-pre+2*se
>
> plot(ts(c(color,pre)), type='l', cex=0.5, xlab='Time', ylab='Color Property', ylim=c(60,90))
Error : The fig.showtext code chunk option must be TRUE
> abline(h=mean(color))
> points(color, col='blue',cex=0.7)
> points(pre, col='red',cex=0.7)
> lines(x=time(pre),y=upBd, col='red', type='l', lty=2)
> lines(x=time(pre),y=lowBd, col='red', type='l', lty=2)
```



- 总结:

1. 小心识别一个初始模型;
  2. 扩展模型时, 不要同时增加AR和MA部分的阶数;
  3. 按照残差分析的建议进行模型扩展;
  4. 利用显著性检验识别冗余参数, 消除过度拟合问题。
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