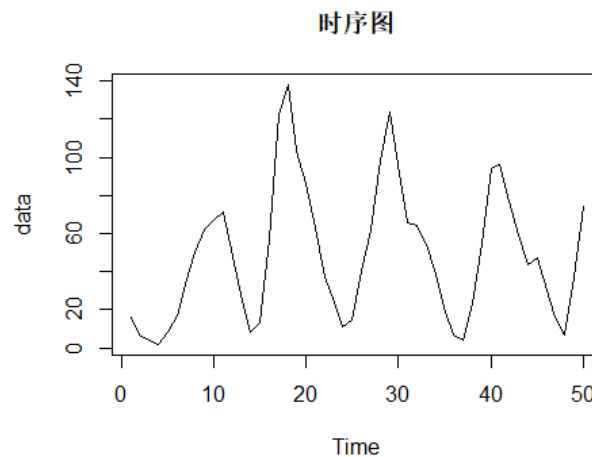


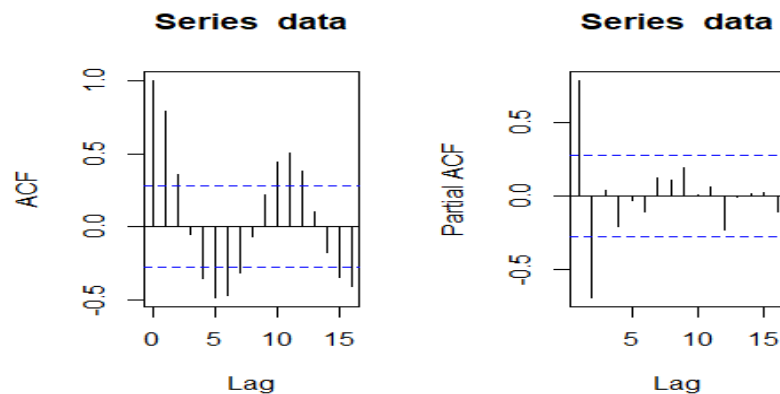
```
library(forecast)

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

data <- ts(read.csv("D:/预删除文件夹/大三下/时间序列/sunpot.csv"))$sunspot)
plot(data)
title("时序图")
```



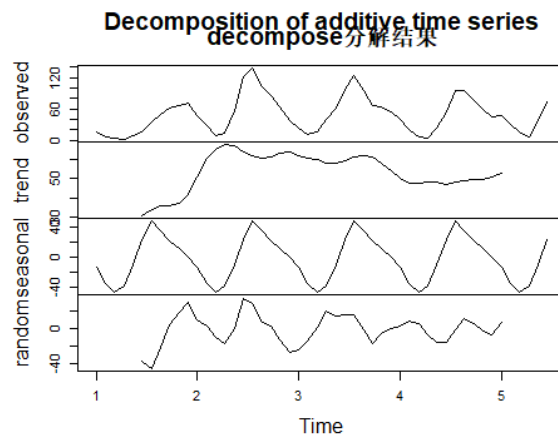
```
par(mfrow=c(1,2))
acf(data)
acf(data,type = "partial")
```



从 ACF 图和 PACF 图来看，推测其可能为 PACF 二阶截尾，但 ACF 图没有表现出明显的拖尾特征，而是表现出显著的周期性，从时序图来看也是明显的周期性序列，故不应该尝试使用 AR 模型或 MA 模型，而是应该对其进行趋势分解

```
data2 <- ts(data,frequency = 11)
model <- decompose(data2)
```

```
plot(model)
title("decompose 分解结果")
```



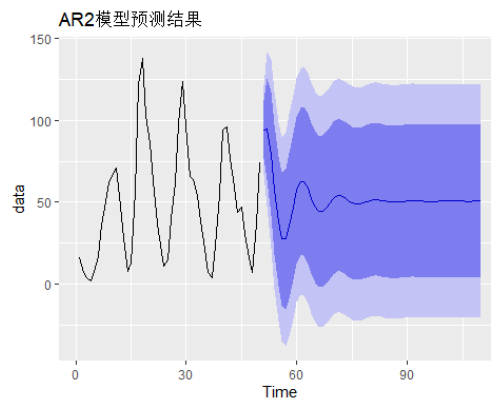
```
Box.test(model$random, lag = 11, type = "Ljung")

##
## Box-Ljung test
##
## data: model$random
## X-squared = 67.826, df = 11, p-value = 3.157e-10
```

从时序图和 ACF 图中观察到太阳黑子的活动大致为 11 年一个周期，故将数据视作周期为 11 的数据，并且波动大小没有明显地随时间变化，故采取加法模型进行分解，结果如上图所示，对随机波动序列作纯随机性检验，结果不佳。下面分别使用 AR(2)模型和 SARIMA 模型进行拟合

```
library(modelsummary)

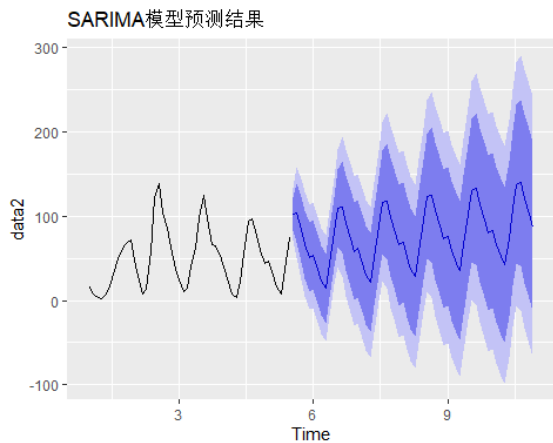
library(ggplot2)
#AR(2)
model2 <- auto.arima(data)
model2 %>% forecast(h=60) %>% autoplot() +
  labs(title = "AR2 模型预测结果")
```



```
Box.test(model2$residuals,lag = 11,type = "Ljung-Box")

##
## Box-Ljung test
##
## data: model2$residuals
## X-squared = 10.891, df = 11, p-value = 0.4524

#ARIMA
model3 <- auto.arima(data2)
model3 %>% forecast(h=60) %>% autoplot() +
  labs(title = "SARIMA 模型预测结果")
```



```
Box.test(model3$residuals,lag = 11,type = "Ljung-Box")

##
## Box-Ljung test
##
## data: model3$residuals
## X-squared = 12.811, df = 11, p-value = 0.3059

modelsummary(list(AR2=model2,SARIMA=model3))
```

	AR2	SARIMA
ar1	1.421	0.593
	(0.088)	(0.176)
ar2	-0.773	
	(0.087)	
intercept	50.640	
	(5.427)	

	AR2	SARIMA
ma1		0.872 (0.345)
drift		0.646 (0.955)
Num.Obs.	50	39
AIC	412.1	331.5
BIC	419.8	338.1
RMSE	13.38	13.06
x	0.85352 9232457 95	0.86620 9426269 778

从上面的结果可以看出二者都在一定程度上较好地提取了序列信息，但从预测结果来看，AR2 模型的平稳性使其预测结果不符合已有观测值的周期性，而 SARIMA 模型较好地拟合了周期性特征