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NEAS Time Series Project

In this projects report, I will include the following section:

- Introduction
- Data
- Model Determination
- Model Fitting
- Model Analysis
- Forecasting
- Appendix: R Code for This Project

Introduction

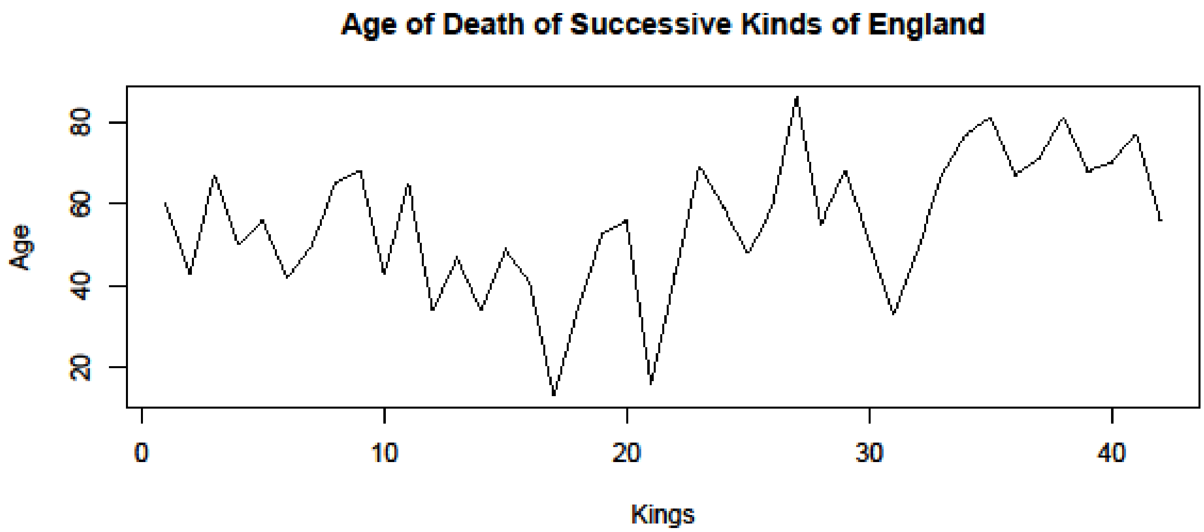
To complete the student project for NEAS Time Series course, I decided to pick the data on the age of death of successive kings of England, starting with William the Conqueror (original source: Hipel and Mcleod, 1994). For statistics software, I used R to get plots and model selection.

Data

The source of the data of age of death of successive kings of England is from the website below:

http://robjhyndman.com/tsdldata/misc/kings.dat

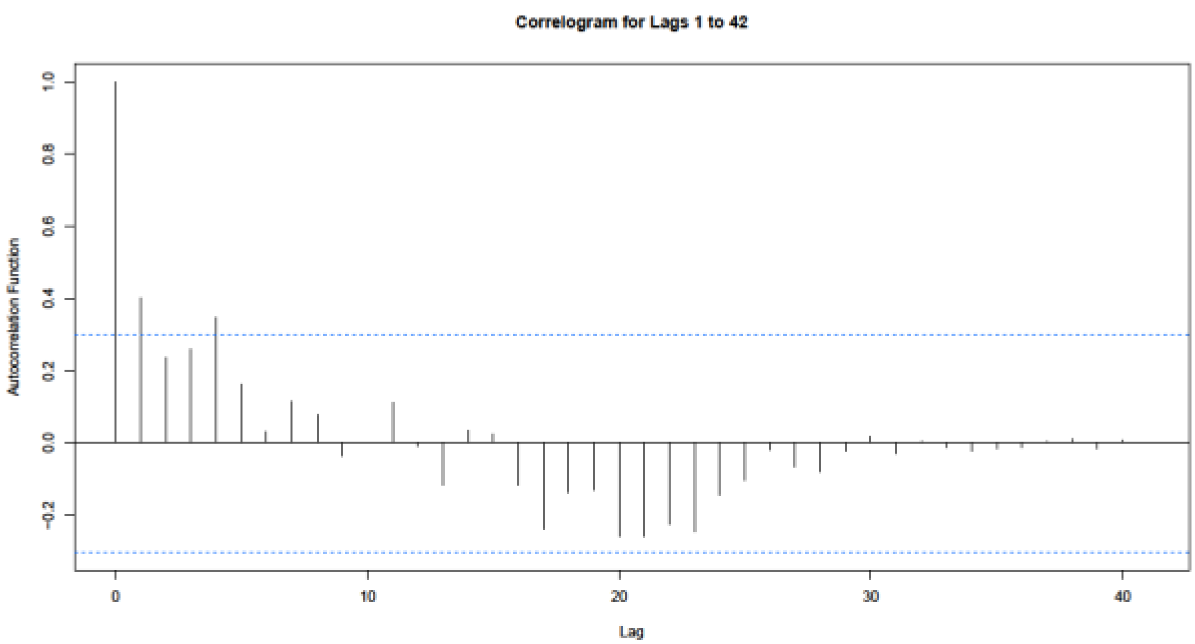
The graph of the data by using R is below:



Model Determination

There is no seasonality on the data. In addition, the time series seems to be stationary in both its mean and variance. As a conclusion, we do not need to difference this data time series in order to fit an ARIMA model, which means, in this case, d = 0.

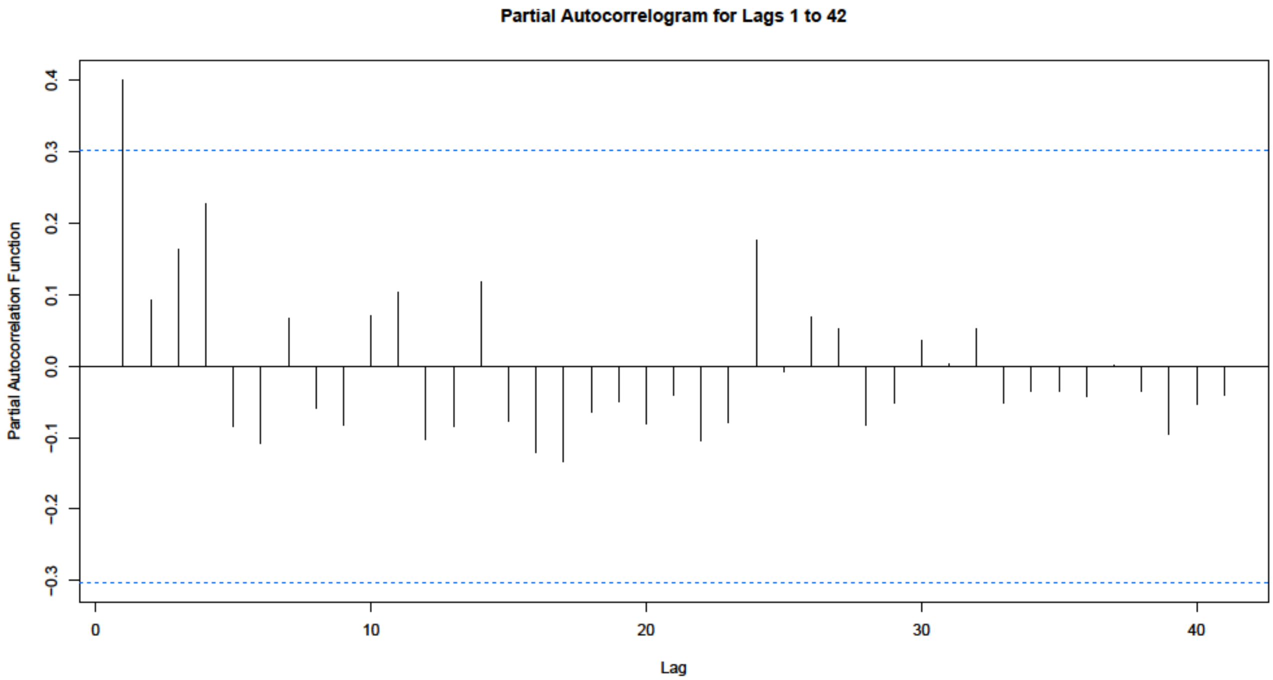
The first model we tried is autocorrelation function. The plot for the age of death time series is shown below:



As it shows in the plot, the autocorrelations for lags 1, 2 and 5 exceeds the significance bound.

The rest of legs remain within the significance bound, and we see both positive and negative fluctuation after lag 5.

The partial autocorrelation function plot for the age of death is shown below:



As it shows in the partial autocorrelation plot that the autocorrelation for lag 1 exceeds the significance bound. The rest of legs remain within the significance bound, and we see both positive and negative fluctuation after lag 1.

Model Fitting

Based on the plot and analysis, the following ARMA models seem suitable for age of death for England Kings time series:

1) An AR(1) model, since the partial autocorrelation decreases to 0 after lag 2.
2) A MA(2) model, since:
   a) MA(2) has fewer parameters than MA(5)
   b) Autocorrelation decreases to 0 after lag 2, except at lag 5.

Model 1: AR(1) model on age of death data

Below is the summary output for an AR(1) model :

AR(1)

Call:

arima(x = kings, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.3921   55.3666

s.e. 0.1392   3.7503

sigma^2 estimated as 224.9: log likelihood = -173.41, aic = 352.82

Model 2: MA(2) model on age of death data

MA(2)

Call:

arima(x = kings, order = c(0, 0, 2))

Coefficients:

ma1   ma2 intercept

0.3732 0.1274   55.3116

s.e. 0.1566 0.1336   3.4602

sigma^2 estimated as 227.8: log likelihood = -173.66, aic = 355.33

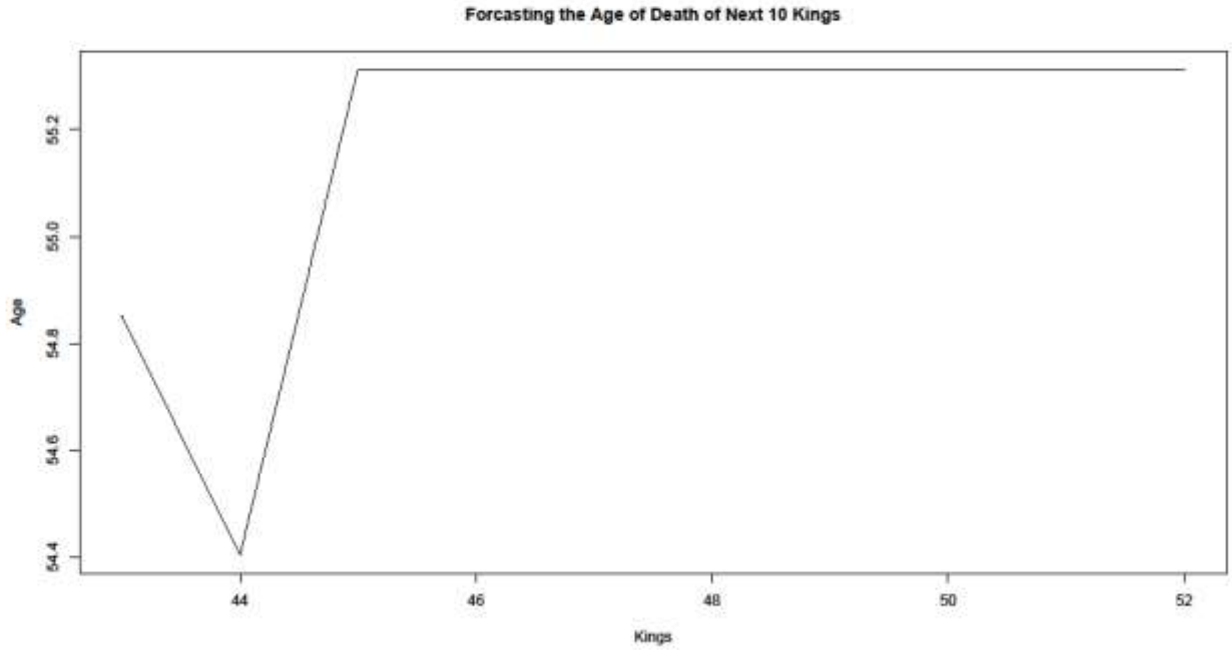
Model Analysis

The AR(1) model has 1 parameters, and the MA(2) model has 2 parameters. By the principle of parsimony, the AR (1) should be selected; nevertheless, an AR model, or autoregressive model, is usually to model a time series that shows long term dependencies between successive observations. The age of death of one king is less likely to have any prediction on the age of death of his successor. Therefore it is more practical to pick MA(2) in this case.

Forecasting

Since the original data includes 42 data points, now I will use MA(2) model to forecast the age of death for the next 10 kinds of England.

The plot is as below:



The forecast shows that for the next kings of England, most of them will die after age of 55 except for the 43^{rd} and 44^{th} whose age of death will be below age of 55.

Appendix: R Code

```
> kings <- scan("http://robjhyndman.com/tsdldata/misc/kings.dat",skip=3)

Read 42 items

> kings

 [1] 60 43 67 50 56 42 50 65 68 43 65 34 47 34 49 41 13 35 53 56 16 43 69 59 48

[26] 59 86 55 68 51 33 49 67 77 81 67 71 81 68 70 77 56

> plot.ts(kings,main="Age of Death of Successive Kinds of England",xlab="Kings",ylab="Age")

> acf(kings,lag.max=42,main="Correlogram for Lags 1 to 42",xlab="Lag",ylab="Autocorrelation
Function")

> pacf(kings,lag.max=42,main="Partial Autocorrelogram for Lags 1 to
42",xlab="Lag",ylab="Partial Autocorrelation Function")

> kings.ma <- arima(kings,order=c(0,0,2))

> kings.ma


Call:

arima(x = kings, order = c(0, 0, 2))


Coefficients:

        ma1     ma2  intercept

     0.3732  0.1274    55.3116

s.e.  0.1566  0.1336     3.4602


sigma^2 estimated as 227.8:  log likelihood = -173.66,  aic = 355.33

> kings.ar <- arima(kings,order=c(1,0,0))

> kings.ar
```

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

Coefficients:
         ar1  intercept
      0.3921    55.3666
s.e.  0.1392     3.7503

sigma^2 estimated as 224.9:  log likelihood = -173.41,  aic = 352.82
> forecast <- predict(kings.ma,n.ahead=10)
> forecast$pred
Time Series:
Start = 43
End = 52
Frequency = 1
 [1] 54.85178 54.40498 55.31160 55.31160 55.31160 55.31160 55.31160 55.31160 55.31160
55.31160
> xvalue <- seq(43,52,1)
> plot(xvalue,forecast$pred,xlab="Kings",ylab="Age",main="Forcasting the Age of Death of Next
10 Kings",type="l")
> >
```