Time Series Analysis

Lecture 4

Mixed Autoregressive Moving Average (ARMA) Models

Autoregressive Integrated Moving Average (ARIMA) Models

Seasonal ARIMA (SARIMA) Models

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Putting Everything Together: ARIMA Modeling

Part 2: Modeling

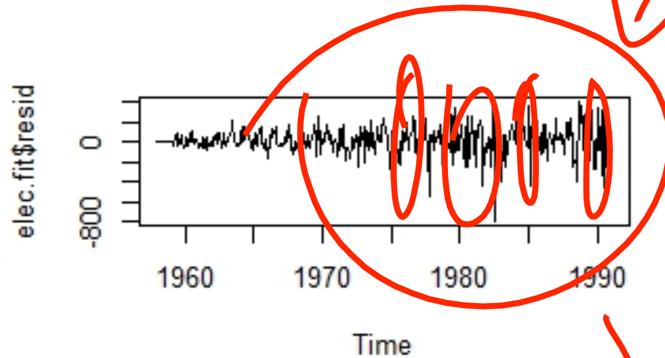
Estimation

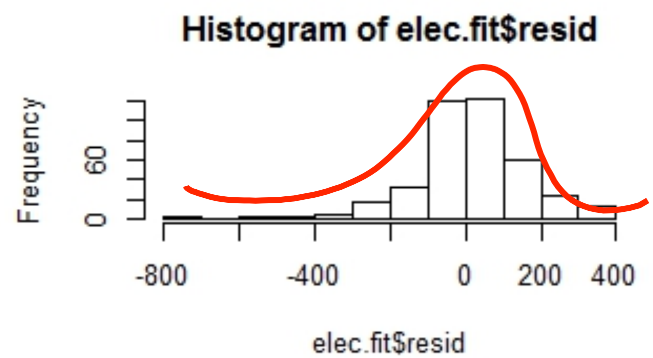
- We will model on the first differenced series, using a seasonal differenced with a MA(1) component and a first differenced with both AR(1) and MA(2) components. We could also run a series of models of small variants of this model.
- All the components are highly significant.

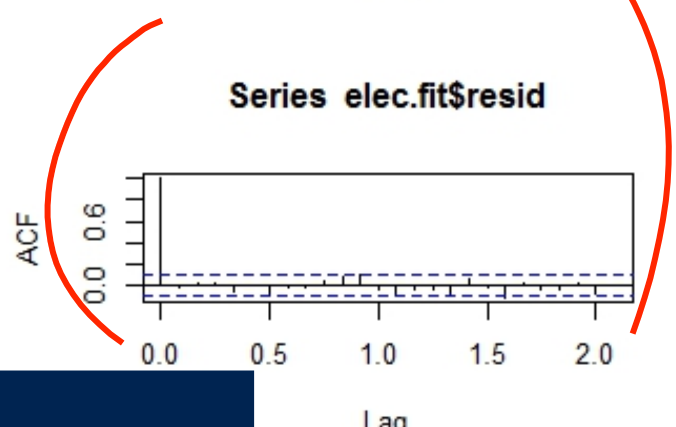
```
> elec.fit <- Arima(elec, order=c(1,1,2), seasonal=c(0,1,1))
> summary(elec.fit)
Series: elec
ARIMA(1,1,2)(0,1,1)[12]

Coefficients:
        ar1     ma1    ma2     sma1
       0.83   -1.48   0.51   -0.537
s.e.   0.11    0.13   0.11    0.044

sigma^2 estimated as 22156:  log likelihood=-2462
AIC=4935   AICc=4935   BIC=4954

Training set error measures:
             ME RMSE MAE MPE MAPE MASE   ACF1
Training set 13  146 105 0.2  1.7 0.33 -0.022
```

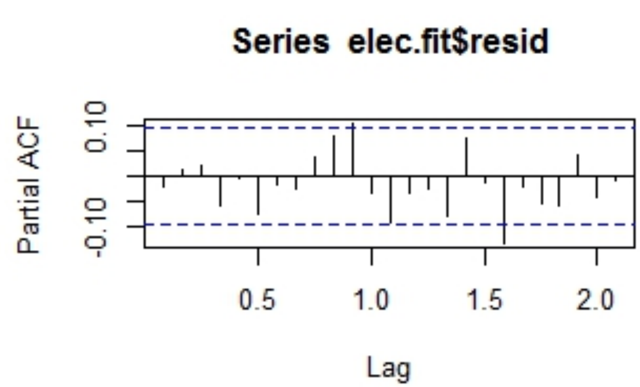
Model Diagnostics Using Residuals

- The residuals clearly increase in volatility over time.
- The distribution of the residuals is skewed.
- However, both the ACFs and PACFs display no significant correlation; Ljung-Box statistic confirms it.





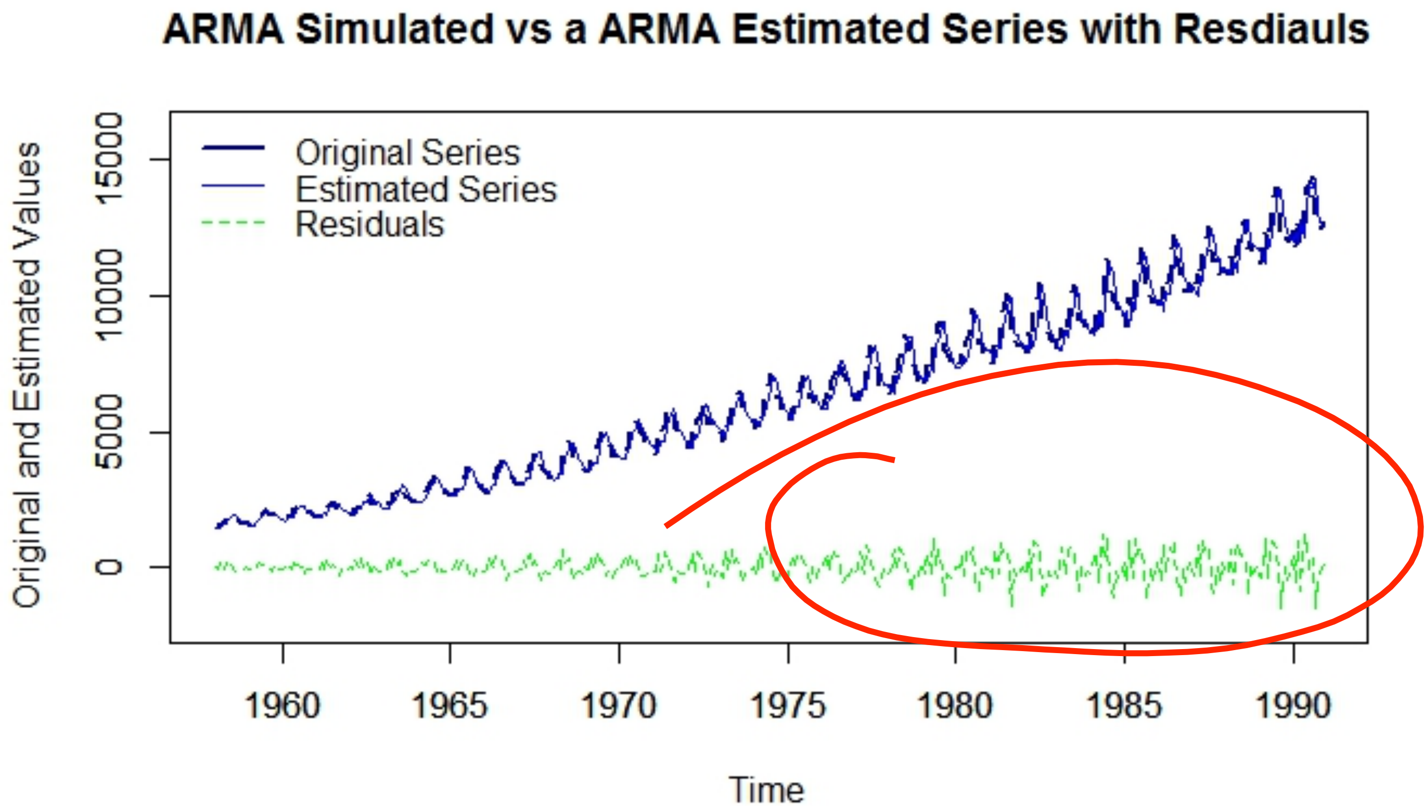





```
 Box-Ljung test

data:  elec.fit$resid
X-squared = 2.6, df = 1, p-value = 0.1062
```

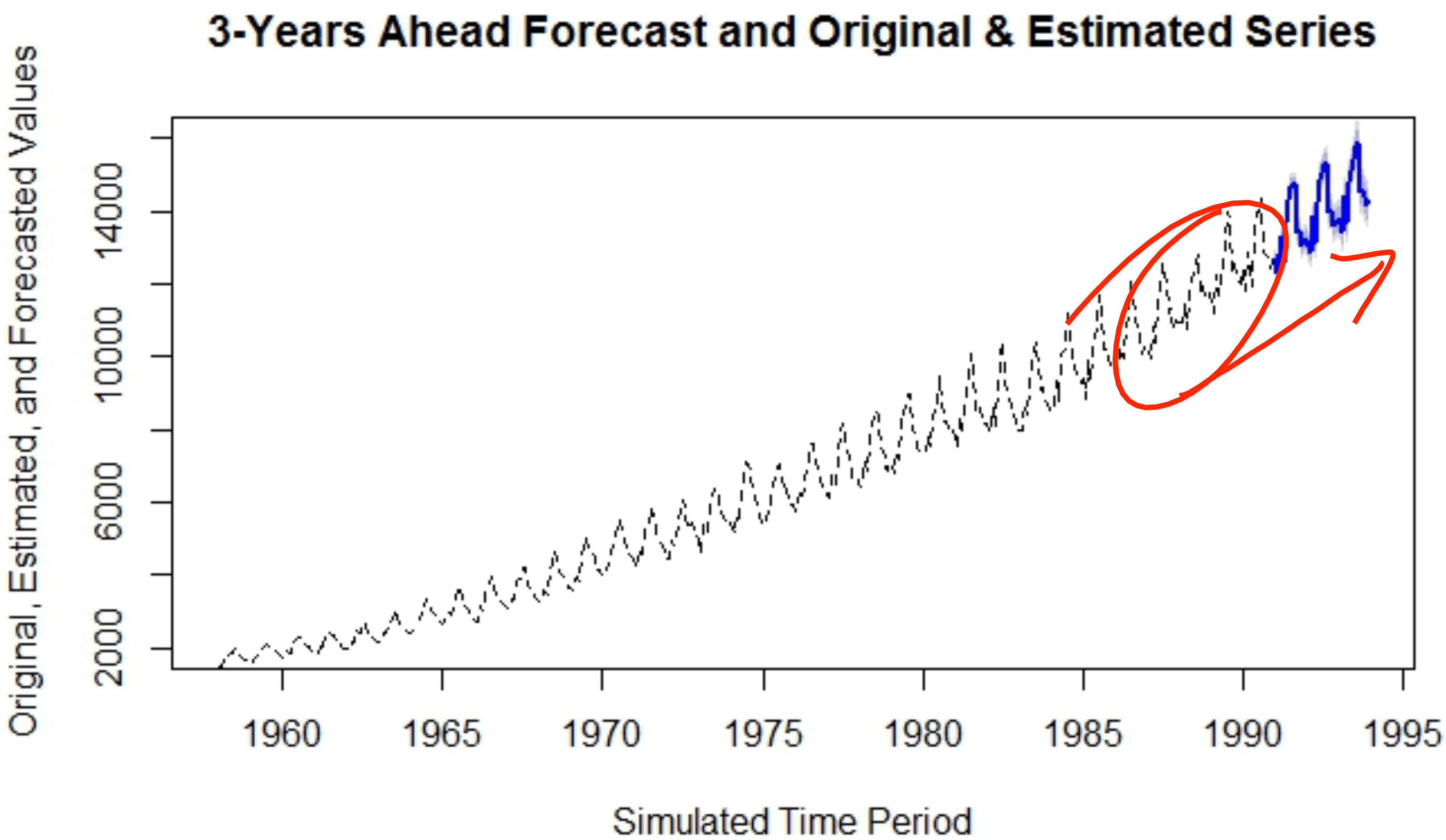
Model Performance Evaluation: In-Sample Fit

- Regardless, we proceed to examine the in-sample fit and forecast using this model, and we will try a series of variants of this model in the R-session.
- The graph below shows an excellent in-sample fit produced by the model.



Forecasting

- The three-year-ahead forecast continues the upward trend and reproduces the seasonal effect embedded in the original series.



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