Summary of ARMA/ARIMA modeling procedures

1. Perform **preliminary transformations**
2. **Detrend** and **deseasonalize**
3. **Difference successively** (at lag 1)
4. **Examine sample ACF & PACF**
5. Obtain **preliminary estimates**
6. Obtain **maximum likelihood estimates**
7. **Choose the ML model with smallest AICC**
8. Use **Autofit**
9. **Fit subset models**
10. Check candidate models for **goodness-of-fit**

Summary of ARMA/ARIMA modeling procedures

1. Perform **preliminary transformations** (if necessary) to stabilize variance over time.

   This can often be achieved by the *Box-Cox transformation*:

   $$f_l(X_t) = (X_t^{\lambda} - 1)/\lambda, \qquad \text{if } X_t \geq 0, \text{ and } \lambda > 0,$$

   $$f_l(X_t) = \log(X_t), \qquad \text{if } X_t > 0, \text{ and } \lambda = 0.$$

   In practice, $\lambda=0$ or $\lambda=0.5$ are often adequate.

2. **Detrend** and **deseasonalize** the data (if necessary) to make the stationarity assumption look reasonable. (Trend and seasonality are also characterized by ACF's that are slowly decaying and nearly periodic, respectively).

   The primary methods for achieving this are ***classical decomposition***, and ***differencing***.

3. If the data looks nonstationary without a well-defined trend or seasonality, an alternative to the above option is to **difference successively** (at lag 1).

   This may also need to be done after the above step anyway.

4. **Examine sample ACF & PACF** to get an idea of potential p & q values.

   For an AR(p)/MA(q), the sample PACF/ACF cuts off after lag p/q.

5. Obtain **preliminary estimates** of the coefficients for select values of p & q.

   For q=0 (pure AR), use *Burg*

   For p=0 (pure MA) use *Innovations*

   For $p\neq0$ & $q\neq0$ (ARMA) use *Hannan-Rissanen*.

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7. From the fitted ML models above, **choose the one with smallest AICC**, taking into consideration also other candidate models whose AICC is *close* to the minimum (within about 2 units).

   The minimization of the AICC must be done one model at a time, but this search can be carried out systematically by examining all the pairs (p,q) such that p+q=1, 2, … , in turn.

   A quicker but rougher method: run through ARMA(p,p)'s, as p=1,2,…, in turn.

8. Can bypass steps 4-7 by using the option **Autofit**. This automatically searches for the minimum AICC ARMA(p,q) model (based on ML estimates), for all values of p and q in the user-specified range.

   Drawbacks:

   a) can take a long time

   b) initial estimates for all parameters set at 0.001

   The resulting model should be checked via preliminary estimation followed by ML estimation to guard against the possibility of being trapped in a local maximum of the likelihood surface.

9. Inspection of the standard errors of the coefficients at the ML estimation stage, may reveal that some of them are not significant.

   If so, **subset models** can be fitted by *constraining* these to be zero at a second iteration of ML estimation. Use a cutoff of between 1 (more conservative, use when few parameters in model) and 2 (less conservative) standard errors when assessing significance.

10. Check the candidate models for **goodness-of-fit** by examining their *residuals*.

    This involves inspecting their ACF/PACF for departures from WN, carrying out the formal WN hypothesis tests, etc.