Model Uncertainty and Forecast Accuracy

Chapter 8 from Chatfield: Time-series Forecasting

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Introduction

- Assumption: 'true' model usually does not exist → find a model that provides an adequate approximation to the given data for the task at hand
- Main sources of uncertainty:
  - Uncertainty about the structure of the model
  - Uncertainty about estimates of the model parameters, assuming the model structure is known
  - Uncertainty about the data when the model structure and the values of the model parameters are known
- Model uncertainty:
  - Structure of the model is misspecified a priori
  - The model parameter are assumed to be fixed when they change through time
  - Formulating, fitting and testing a model using the same set of data

Model building

- Box-Jenkins model building procedure:
  - Iterative cycle of model specification, model fitting, and model checking
  - Typical forecasting application:
    - Choice of plausible family of possible models
    - Look at a time plot of the data and at various diagnostic tools
    - Choice of the ‘best’ model and computation of inferences, forecasts
  - Usually analysts look at many different models
  - Strategies in data-analysis procedure:
    - Excluding, down-weighting, adjustment of outliers
    - Transforming one or more variables
  - Model-selection bias:
    - Model is formulated and fitted to the same data

Data dredging

- It is a process of selecting a model from a large set of candidate models and then using it for inference and prediction
- Alternative:
  - Data-driven inference
- Pretesting various hypotheses indicates awareness of model uncertainty
- Note:
  - Inference following model testing is biased
  - Testing implicitly assumes the existence of a true model is included in the set of models entertained
  - The more models that are entertained, and the more tests that are carried out, the lower the chance of choosing the ‘correct’ model
- So, a model is seen as a useful description of the given data and hence the context and the objectives are key factors in model building

Inference after model selection

- Assumption: ‘true’ model does not exist usually
- Properties of an estimator may depend, not only on the selected model, but also on the selection process

- Prediction intervals are too narrow:
  - Residual variance and PMSE are underestimated
  - Wrong model may be identified or the model may change through time
  - Predictive variance (affected by parameter/model uncertainty)
    - Example: AR(1) – stationary or non-stationary
- Computational studies – simulation of model-selection procedures:
  - Hjorth (1987), Pötscher and Novak (1998), Faraway (1992), Sauerbrei (1999)
- Model checking:
  - Diagnostic tests – hardly reject the best-fitting time series model

Coping with model uncertainty

- Choosing a single model:
  - Local or global model?
    - Allowing for changing model structure and model parameter values or not?
    - Kalman filter (exponential smoothing)
  - Simple or complicated?
    - Principle of Parsimony
    - Reduce bias or decrease variance
  - Is the method robust?
    - Can the forecasting method adapt to changes in the underlying model structure?
    - Can the method give good forecasts in practice?
    - Sensitivity analysis

- Using more than one model:
  - Scenario analysis:
    - Used in long-range forecasting
    - Different models rely on different assumptions about the future
  - Combine forecasts from different methods and models:
    - Often more accurate than individual forecasts
    - Difficult to compute prediction intervals
  - Different models for the description of different parts of the data:
    - E.g. Seasonal model should describe the seasonality in the data
  - Different models for different lead times:
    - Short-term vs. Long-term forecasting models
  - Bayesian model averaging:
    - Model selection is based on prior knowledge and prior probabilities
    - Models with low posterior probabilities may be discarded
    - Combined forecast is expected to have a lower PMSE
    - Problem: specification of prior probabilities is not easy
    - It is good for description and interpretation and not for forecasting

- Check out-of-sample forecast accuracy with data splitting:
  - Ideal way to test a model is to check forecast accuracy on a completely new set of data → usually not immediately available → data splitting:
    - Fitting the model to the first part (construction, training or calibration sample)
    - Using the second part (hold-out, test or validation sample) to check inferences and predictions
  - Problem: how to split the data?
    - Analysts typically 'hold back' about 10% of the data
- Handling structural breaks:
  - 2 issues:
    - How to detect a structural break in past data and how to respond when such a break does occur?
    - It is possible to anticipate a structural break and how should then forecasts be made?
  - Ideal type of predictor: causally related to the output and cointegrated with it through sudden changes
  - Sudden changes may become clear few periods/observations after the break
  - Tests for structural break need careful specification and many observations after the change
  - Multivariate models may forecast structural break
  - In case of structural break, use intervention effect, difference the data or fit a different intercept before and after the change

Summary

- Classical theory generally assumes that a ‘true’ model for a given set of data is known and pre-specified
- Many models may be entertained and a single model is usually selected
- Main message: when a time-series model is formulated and fitted to the same data, then inferences and forecasts made from the fitted model will be biased and seriously over-optimistic when the prior data-dependent model-selection process is ignored

- Standard least-squares theory does not apply when the same data are used to formulate and fit a model. Estimates of the model parameters, including residual variance, are likely to be biased.
- Models with more parameters may give a better fit, but worse out-of-sample predictions. Thus, when comparing the fit of different models, a measure of fit must be used that penalizes the introduction of additional parameters. AICc and BIC is recommended for choosing time-series forecasting models.
- The analyst typically thinks the fit is better than it really is, and prediction intervals are too narrow, partly because residual variance tends to be underestimated and partly because prediction intervals fail to take full account of model uncertainty.
- Bayesian model averaging offers a promising approach to cope with model uncertainty. However, there is no simple general ‘fix’ approach/method to cope with model uncertainty.

Thank you for your attention!