



Model selection



Data to decisions

The problem

- Which model is best **for the purpose of answering a particular question?**
- Say, for concreteness, for forecasting purposes
- You could say that getting as close to the true DGP as possible is the obvious goal
- Yet:
 - There is no hope of knowing the true DGP in any interesting problem
 - Among misspecified models, models closer to the true DGP may forecast more poorly
 - Or, more generally, models closer to the true DGP can be worse for the purpose of answering the question at hand



Context matters

- “Models are rats”
- (See Kocherlakota’s ‘Model Fit and Model Selection’, St-Louis Fed review, April 2007)
- Models are wrong but, hopefully, useful for the specific purpose at hand
- But we should be able to rank alternatives: **model selection is model comparison**



Is fit the answer?

- Why not use the model that fits the evidence best for forecasting purposes?
 - Fit can always be improved by adding more variables...
 - ... even variables that have nothing to do with the true DGP but happen to correlate with random draws in the sample at hand
 - In fact, maximizing fit would invariably lead one to add variables that matter in sample through chance only and will hurt forecasting performance
 - This is called *overfitting*
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General principles

- There is a tradeoff between fit and parsimony
- **Principle #1:** among models that fit (=explain) about the same choose the more parsimonious one
- **Principle #2:** reward fit but penalize complexity (wiki information criterion)



Cross-validation

- If our purpose is to forecast, forecasting ability is the right criterion to use
- How can one test forecasting ability since, by definition, we do not know what the right answer is?
- Answer: split your sample into an estimation/training sample and a test sample
- Estimate your model on estimation model, evaluate how the model predicts the test sample
- Criterion: RMSE (mean squared error)



Warning

- Designing a model that fits historical evidence is trivial
- Forecasting is tough
- More complex models fit better, but forecast poorly (Wiki “overfitting”)
- Only criterion that matters: out-of-sample forecasting fit
- In other words, how has your forecast performed?
- Truth: beating naïve models is tough, and naïve models are free



Information criteria

- Information criteria are quantitative measures of a model's performance in the fit/parsimony space
- Example: Akaike's information criterion (AIC)

$$AIC = 2k - 2 \log(L)$$

where k is the number of parameters and L is the likelihood of the data under the model

- Some do model selection simply by ranking models according to information criteria (= picking the model with the lowest AIC)
- Meh...



But enough chit-chat, it's time to look at some examples

