The Promise and Limits of Machine Learning and Big Data in Macrofinance

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Outline

1. Machine learning and big data comments
   a) Prediction versus causation
   b) Virtues of agnostic black-box modeling?
   c) Big Data
   d) Lucas Critique

2. Brief comments on Giesecke, Sirignano, Sadhwani
Why Machine Learning?

• Kleinberg, Ludwig, Mullinaithan, Obermeyer (2015 AER P&P) answer:
  • Prediction vs causation
    – Umbrella (FICO) vs. rain dance (monetary policy)
    – Risk management vs. regulation?
    – Variance vs. bias
    – Can prediction inform causation?
  • As academics, need a lot of help to care about predictions instead of “how the world works”
    – Not content with a kitchen sink regression, we want to understand mechanisms
Value of Models

• Kay’s answer on value of machine learning:
  1. To handle big data
  2. To handle “true” model’s unknown nonlinearities
• “All models are wrong, some models are useful.” – George Box
• “The art of modeling is what you leave out.” – Bengt Holmstrom
• Promise of machine learning is that we won’t need our woefully simplistic models.
• But w/o models, we also don’t really gain any understanding.
• If we’re lucky, we’ll gain enhanced predictive power.
• This is no substitute for modeling—it is just for a different purpose than prediction.
Lucas Critique

• Key worry, inspired by “The Failure of Models that Predict Failure,” Rajan, Seru, Vig (2015 JFE)
• When we are interested in prediction instead of causation, we always have to be concerned with the stability of that model.
• Teaching to the test ⇔ Lending to the test
• Given the data requirements of machine learning, hard to assess model drift over time.
Big Data: No Substitute for Identification

• Helps with: power, weak instruments, local effects, etc.
• **Not** selection bias, measurement error, endogeneity
• Worry can be thought of as external validity:
  • Yes, can get significant coefficients with $R^2 < .0001$ if sample large enough...
  • But if pattern only really applies to a very small subset of a very large dataset, have we really learned anything general?
• Estimated treatment effects start to look like very very local treatment effects.
“Deep Learning for Mortgage Risk”
Giesecke, Sirignano, and Sadhwani

• **Goal**: Improve risk management by leveraging machine learning and big data.

• **Real goal**: Demonstrate proof-of-concept handling breadth and depth of loan-level data for perfect applications yet unspecified.

• **Research Question**: Can machine learning techniques outperform logit predictions of defaults?
  – *NOT* does X cause default, will macropru foster robust loans, is a crisis coming, etc.

• **Method**: Compare predictions out of sample for both methods.
Why Machine Learning Here?

1. To handle big data. Why not a sample?
   – Once you look within zip codes, 120m nationwide becomes small.
   – Nonparametric methods are data hogs: “Curse of Dimensionality”
   – For rare events especially, need sufficient failures

2. To improve predictions via neural networks modeling
Prediction Improvements

• Even regularized multinomial logit can predict default state with high degree of accuracy (99%).
• Hardest: predict voluntary prepayment. (Logit 65%)
  – Fundamental problem for risk management, pricing of RMBS...
• Successfully predict voluntary prepayment 9 percentage points better (74% of time) than multinomial logit
  – All other performance states: 0-1 p.p. improvement
• Not done yet. Can do one-month predictions. What horizon is most important for risk management? Stress testing?
• Improvement in false positives or false negatives?
Value Added Predicting Prepayment

Out of Sample State Prediction Improvement

Prediction Improvement over Logit (percentage)
Conclusion

• We’ve seen mostly proof-of-concept papers in machine learning + macrofinance.
• Not their fault; should be eye opening. Nontrivial next step is to demonstrate the golden application that teaches us something new about the macroeconomy.
• To facilitate adoption of these methods, hold our hands to help us see what research questions can uniquely be answered with these methods, as opposed to their use in predictive analytics.
  – See Varian (2014) for some of this hand holding.