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

Discussion by Christopher Palmer
University of California, Berkeley

MFM Winter Meeting

January 29, 2016
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 presentations
   a) Giesecke, Sirignano, Sadhwani
   b) Wallace

3. Big data in action: transmission of QE
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: Whitney Newey’s “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
ICYMI, Nancy’s 5 Points

1. High stakes in this arena: Poterba quote
2. Mortgage contract features jointly endogenous => proceed at your own risk
3. Observing whole “contract space” requires non-trivial merges/assembling, but can be done
4. Systemic risk picture different when you observe lending networks
5. Repeat-sales indices mask volatility and are biased in the presence of frequent renovations.
Importance of Entire Contract Space

- "Mortgage origination is a high-dimensional contracting problem so most contract elements are jointly endogenous."
- => why we can't “fix” things by having outlawing particular contract features that seems to be most predictive of bad outcomes.
- Dodd-Frank does things like outlaw/restrict long mortgage maturity, prepayment penalties, low-documentation, high DTI, etc.
- If selection (not treatment effect of that contract feature)
  - Best-case scenario: restricting it doesn’t change aggregate outcomes it just buries/pools those outcomes with others
  - Worst-case: it restricts access to credit markets based on faulty empirics.
Integrated Data in Action

• Disclaimer: Self-promoting discussants
• “Unconventional Monetary Policy and the Allocation of Credit” (with Marco Di Maggio and Amir Kermani)
• Goal: Understand transmission of unconventional monetary policy and its heterogeneous beneficiaries
• Focus: How RMBS purchases affect lending
Why Integrated Database Necessary?

• First-order effect of Fed TBA purchases was to lower GSE mortgage rates.

• How did mortgage volumes change?
  – Identification requires rich microdata for strategy that exploits mortgage market segmentation (CLL, LTV) and controls for borrower and mortgage note heterogeneity

• Who were the borrowers that benefitted?
  – Requires linking mortgage spells within a borrower

• Who were the banks that benefitted?
  – Requires understanding banks’ balance sheets, lending networks, RMBS holdings
CLL Bunching to “Take-up” QE

# of Loans 61502, Bunching Rate: 43%, Average Cash-In: $26.2k

Density

Loan Amount After Refinancing/CLL

Loan Amount Before Refinancing/CLL
Unconventional MP Transmission

• Direct lending channel – during QE1, Fed essentially bypassing banks to inject liquidity directly into household sector.

• How do we know this? Other segments of the market clamored to crowd into GSE segment that was the direct beneficiary of QE purchases.

• Integrated data allows us to view entire mortgage ecosystem.
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.