Machine Learning and Central Banks: Ready for Prime Time

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Introduction

- Advances in artificial intelligence research has transformed many tasks previously carried out 'manually'.
  - Credit scoring, interpreting X-ray images, translation, and facial recognition and many other...
  - COVID-19 era: more automation?
- Holds up the promise of being able to give us driverless cars.

- Central banks ask: Can these methods be used to cater to the needs of central banks?
- If algorithms/computers can be trusted to drive cars, trucks and buses - can computers also be trusted with some aspects of the conduct/advice of monetary policy?

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This presentation

- Disclaimer: We are not ML experts - have experience and interest in central banking/macro policy.
- We will have two things in the background when we consider the ML for central banking (monetary policy to be more precise):
  1. What does a monetary policy making authority do in the process of policy making?
  2. The development of the VAR/SVAR literature:
     - VARs/SVARs and their variants are workhorse models in answering central bank's questions/needs
- We will then use the S/VARs as a lens through which to observe, analyse and/or speculate if the machine learning can help in the process of monetary policy making.

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We will then argue/conclude/speculate

- CBs can look at the contributions of the VAR lit and ask for/expect similar contributions from ML.
- In that sense, ML is a long way away from answering the needs of CBs.
- However, there are promising avenues.

What do central banks do?

- Adapt the Stock and Watson (2001) classification to central bank policy making.

  1. Central banks summarise and analyse data,
  2. They forecast the key macroeconomic variables,
  3. They conduct risk analysis and balance of uncertainties.
  4. They do structural/causal analysis, as well as scenario analysis.
  5. They take decisions and communicate and justify these decisions vis-a-vis the public.

- (1) - (5) also in the spirit of Sims (1980).
- He argued that the usefulness of VARs could come from three fronts: (1) forecasting macroeconomic variables; (2) designing and evaluating economic models; (3) evaluating the consequences of alternative policy actions.

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Why VARs as the LENS?

- It is an empirical toolkit (like the ML) that has served us well over the past 40+ years.
- Adjusted for and adapted to the needs of the CBs/policymaker over the decades.
- Not a black-box and can be communicated easily.
- Can be related to economic theory (shocks) (unlike the current use of ML).
- Can be combined with judgement (defeats the ML purpose?)
- We believe, it is a good lens through which one can think about the ML.

Pagan Frontier

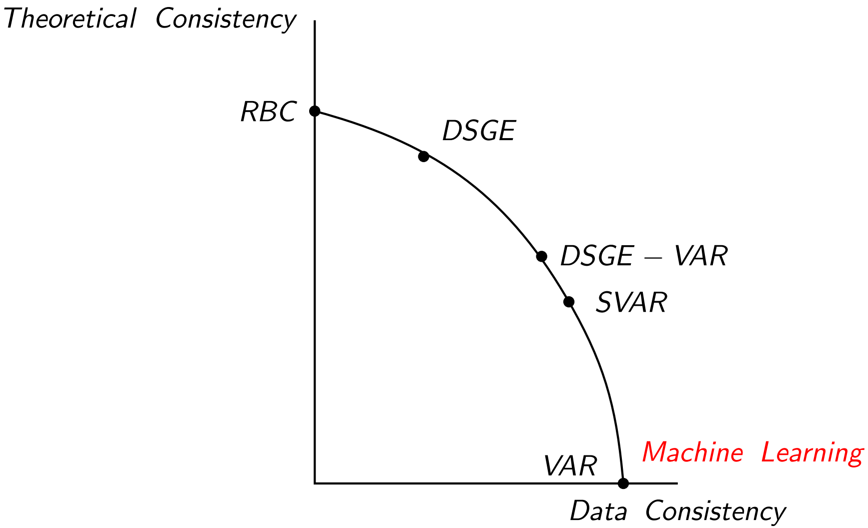

Figure 1: The Pagan Frontier

Machine Learning

- There does not appear to be any broad consensus on the precise definition of machine learning.
- Machine Learning (ML) has its origins in computational statistics.
- Its primary concern has been the use of algorithms to identify patterns or interrelationships in data and using these patterns in prediction.
- While the algorithms used in ML can be common household names such as the OLS or much more complex methodologies such as multilayer neural networks, the main focus remains to be on prediction.
- The growing popularity of ML comes from its ability to uncover complex patterns that have not been pre-specified a priori.

Machine Learning

- In forecasting inflation, for example, researchers usually start with a pre-determined, typically linear, structure that comes from theory.
- But if forecast accuracy is the prime goal, this pre-specified structure can be a weakness.
- The advantage of machine learning is that it does not have to impose it on the estimation of the model and hence on the forecast.
  - Deep learning neural network algorithms do not impose any particular functional form of the relationship between the explanatory variables and the forecast target.
  - Instead this functional form is the outcome of the network algorithm.
- Note that the algorithms themselves my favor some functional forms over others by construction, a feature referred to as inductive bias Kelleher (2019).
- Methods developed in the ML literature have been particularly successful in "big data" settings.

VARs in Forecasting

- The variants: time-varying parameters, stochastic volatility, regime switching.
- Bayesian variants with priors/shrinkage provide very good forecasts.
- Recently, density forecasting, tail forecasting: (including asymmetric densities): Carriero et al. (2020)
- What to do with COVID-19 observations? Primiceri and Tambalotti (2020)
- Recently, monetary policy makers become interested in the tail-risks (Adrian et al. (2019)) - the VAR literature adapted to the new environment:
- Chavleishvili and Manganelli (2019) extended this framework in a VAR context (Quantile VARs)

ML in Prediction

- ML in macro is mostly but not exclusively about prediction so far.
  - Macro forecasts are univariate.
- Forecasting with ML has a large cross-sectional element.
- However, the improvement in forecasting accuracy appear to be non-negligible.
- Yet to be seen how ML forecasts will stand against the large structural change COVID-19

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Structural Analysis

- Central banks are interested in "structural/causal" questions. Because we forecast and then 'intervene'.
- To give a VAR a structural interpretation we need to impose restrictions on the model so that we can recuperate the structural shocks.
- A very large literature has evolved to do just that.
- Why structural identification? To give the resulting VAR impulse responses, forecast error variance decompositions, and historical decomposition economic meaning.
- Distributional effects: Chang et al. (2021) - fVAR

Giving VARs a structural interpretation

- There are a number of potential sources - adjusted from Kilian and Lutkepohl (2018):
  - Theoretical consistency.
  - Information delays.
  - Physical constraints.
  - Institutional knowledge.
  - Assumptions about market structure.
  - Homogeneity of demand functions.
  - Extraneous parameter estimates.
  - High-frequency data.

Here we see huge opportunities for ML

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ML in identification - VARs

- Can ML help us with identification in SVARs?
- Can ML for example estimate the elements of the A_0 in SVAR?
- Factors as instruments. ML estimates as instruments?

ML in identification - Causal Inference

- To our knowledge, the current ML algorithms are at infancy in terms of penetration into the macro literature.
- These algorithms are often characterized as 'black boxes', although there is an emerging literature on interpretable machine learning algorithms (Molnar et al. (2020)).
- This avenue of identification has been gaining momentum in other fields of economics, and we see this as an exciting opportunity that will eventually arrive in macro issues. Moreover, we also see the potential of this line of identification marrying the structural VAR way of identification.
- So in this sense, works by Pearl (2018) and Pearl and Mackenzie (2018) can become useful for central banking in the future especially combined with the big data sets that the central banks are using more and more actively (Doerr et al. (2021)).

An example of ML in causal inference

- Employment effects of minimum wage policy. Question: does it make things worse for the same people by destroying jobs?
- A major difficulty is precisely identifying the workers who are affected by the policy. Hence the focus on specific demographic groups or industries (teens or the fast-food sector).
- Cengiz et al. (2021) uses machine learning tools to predict which individuals were likely affected by minimum wage increases.
- This is a prediction exercise, and they use three main tree-based learning tools: decision trees, random forests and gradient tree boosting.
- They validate that the model can successfully construct a group containing more than 73 percent of minimum wage workers.

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Communications

- Central Banks need to communicate their policy decisions, especially monetary policy decisions: 1) Accountability and 2) Credible communication can make the policy more powerful
- Communication includes - risks, uncertainty
- VARs are rather adaptable tools: CBs want to communicate uncertainty with fan charts: VARs can handle them
- CBs want to communicate skew in risks, again VARs are adjusted to be able to handle this.

Communications

- Central banks need to be able to 'tell a coherent story' when they communicate the results of their models and forecasts
- For example, a central bank might have a certain view based on an empirical or model based evidence that the house prices affect the economy in a particular direction.
- This would bring a lot of challenges to the communications of ML based forecasts. First, they are complicated.
- However, the complexity already exists in the types of models many central banks use.
- Second, the what the algorithm picks in this year might differ next year, which might create many communications challenges.

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Conclusions

- The VAR toolkit in central banks: forecasting, structural analysis, scenario analysis, density analysis, tail analysis.
  - Adaptable: QVAR, OccBin SVAR, fVAR..
- If our thesis is correct, and for machine learning models to be adopted widely by central banks in their monetary policy toolboxes, their causal structure and interpretation need to become more transparent (easier to communicate).
- Data Science Teams/Departments need macro/monetary economists as well as data scientists/computer scientists
- ML has so far not evolved to provide answers in many dimensions that matter for central banks.
- It is unfair and premature to expect the machine learning to deliver answer in these within a quick time frame: It will take time, but we are hopeful

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