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Personal Information:

Date of Birth: 1992
Citizenship: Canadian

Undergraduate Studies:

BA, Economics, Université Laval, Québec City, 2014

Masters Level Work:

MA, Economics, Queens University, Kingston, 2015
Essay : *A Fractionally Cointegrated VAR Analysis of Price Discovery and Financial Integration*
Supervisor: James G. MacKinnon

Graduate Studies:

University of Pennsylvania, 2016 to present
Thesis Title: *Machine Learning Econometrics*
Expected Completion Date: May 2021

Thesis Committee and References:

Professor Francis X. Diebold (Co-advisor), University of Pennsylvania
Contact: 215-898-1507, fdiebold@econ.upenn.edu

Professor Frank Schorfheide (Co-advisor), University of Pennsylvania
Contact: 215-898-8486, schorf@econ.upenn.edu

Professor Karun Adusumilli, University of Pennsylvania
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Professor Dalibor Stevanovic, Université du Québec à Montréal
Contact: 1-514-987-3000 # 8374, dstevanovic.econ@gmail.com

Teaching and Research Fields:

Econometrics, Machine Learning, Macroeconomics, Climate Change

Teaching Experience:

Recitation Instructor for Econ 103 (Statistics for Economists)
Semesters: Fall 2017, Spring 2018, Fall 2018, and Spring 2019
Professors: Karun Adusumilli, Francis DiTraglia, Suleyman Ozmucur

Research Experience and Other Employment:

- Research Assistant for Professor Francis X. Diebold (Penn) 2019-
- Research Assistant for Professor Ioana Marinescu, (Penn) 2018
- Economist, Economic Studies and Policy Analysis, (Department of Finance Canada) 2015-16

Publications:

Optimal Combination of Arctic Sea Ice Extent Measures: A Dynamic Factor Modeling Approach
(In Press, International Journal of Forecasting)
with Francis X. Diebold, Maximilian Göbel, Glenn Rudebusch and Boyuan Zhang

The diminishing extent of Arctic sea ice is a key indicator of climate change as well as an accelerant for future global warming. Since 1978, Arctic sea ice has been measured using satellite-based microwave sensing; however, different measures of Arctic sea ice extent have been made available based on differing algorithmic transformations of the raw satellite data. We propose and estimate a dynamic factor model that combines four of these measures in an optimal way that accounts for their differing volatility and cross-correlations. We then use the Kalman smoother to extract an optimal combined measure of Arctic sea ice extent. It turns out that almost all weight is put on the NSIDC Sea Ice Index, confirming and enhancing confidence in the Sea Ice Index and the NASA Team algorithm on which it is based.

Working Papers:

The Macroecononomy as a Random Forest **(Job Market Paper)**

I develop *Macroeconomic Random Forest* (MRF), an algorithm adapting the canonical Machine Learning (ML) tool to flexibly model evolving parameters in a linear macro equation. Its main output, *Generalized* Time-Varying Parameters (GTVPs), is a versatile device nesting many popular nonlinearities (threshold/switching, smooth transition, structural breaks/change) and allowing for sophisticated new ones. The approach delivers clear forecasting gains over numerous alternatives, predicts the 2008 drastic rise in unemployment, and performs well for inflation. Unlike most ML-based methods, MRF is directly interpretable – via its GTVPs. For instance, the successful unemployment forecast is due to the influence of forward-looking variables (e.g., term spreads, housing starts) nearly doubling before every recession. Interestingly, the Phillips curve has indeed flattened, *and* its might is highly cyclical.

Time-Varying Parameters as Ridge Regressions (submitted)

Time-varying parameters (TVPs) models are frequently used in economics to model structural change. I show that they are in fact ridge regressions. Instantly, this makes computations, tuning, and implementation much easier than in the state-space paradigm. Among other things, solving the equivalent dual ridge problem is computationally very fast even in high dimensions, and the crucial "amount of time variation" is tuned by cross-validation. Evolving volatility is dealt with using a two-step ridge regression. I consider extensions that incorporate sparsity (the algorithm selects which parameters vary and which do not) and reduced-rank restrictions (variation is tied to a factor model). To demonstrate the usefulness of the approach, I use it to study the evolution of monetary policy in Canada. The application requires the estimation of about 4600 TVPs, a task well within the reach of the new method.

To Bag is to Prune (submitted)

It is notoriously hard to build a bad Random Forest (RF). Concurrently, RF is perhaps the only standard ML algorithm that blatantly overfits in-sample without any consequence out-of-sample. Standard arguments cannot rationalize this paradox. I propose a new explanation: bootstrap aggregation and model perturbation as implemented by RF automatically prune a (latent) true underlying tree. More generally, there is no need to tune the stopping point of a properly randomized ensemble of greedily optimized base learners. Thus, Boosting and MARS are eligible for automatic (implicit) tuning. I empirically demonstrate the property, with simulated and real data, by reporting that these new completely overfitting ensembles yield an out-of-sample performance equivalent to that of their tuned counterparts – or better.

Arctic Amplification of Anthropogenic Forcing: A Vector Autoregressive Analysis
(R&R, Journal of Climate), with Maximilian Göbel

Arctic sea ice extent (SIE) in September 2019 ranked second-to-lowest in history and is trending downward. The understanding of how internal variability amplifies the effects of external CO2 forcing is still limited. We propose the VARCTIC, which is a Vector Autoregression (VAR) designed to capture and extrapolate Arctic feedback loops. VARs are dynamic simultaneous systems of equations, routinely estimated to predict and understand the interactions of multiple macroeconomic time series. Hence, the VARCTIC is a parsimonious compromise between full-blown climate models and purely statistical approaches that usually offer little explanation of the underlying mechanism. Our "business as usual" completely unconditional forecast has SIE hitting 0 in September by the 2060s. Impulse response functions reveal that anthropogenic CO2 emission shocks have a permanent effect on SIE - a property shared by no other shock. Further, we find Albedo- and Thickness-based feedbacks to be the main amplification channels through which CO2 anomalies impact SIE in the short/medium run. Conditional forecast analyses reveal that the future path of SIE crucially depends on the evolution of CO2 emissions, with outcomes ranging from recovering SIE to it reaching 0 in the 2050s. Finally, Albedo and Thickness feedbacks are shown to play an important role in accelerating the speed at which predicted SIE is heading towards 0.

How is Machine Learning Useful for Macroeconomic Forecasting? (submitted)
with Maxime Leroux, Dalibor Stevanovic and Stéphane Surprenant

We move beyond "Is Machine Learning Useful for Macroeconomic Forecasting?" by adding the "how". The current forecasting literature has focused on matching specific variables and horizons with a particularly successful algorithm. In contrast, we study the usefulness of the underlying features driving ML gains over standard macroeconometric methods. We distinguish four so-called features (nonlinearities, regularization, cross-validation and alternative loss function) and study their behavior in both the data-rich and data-poor environments. To do so, we design experiments that allow to identify the "treatment" effects of interest. We conclude that (i) nonlinearity is the true game changer for macroeconomic prediction, (ii) the standard factor model remains the best regularization, (iii) K-fold cross-validation is the best practice and (iv) the L2 is preferred to the $\bar{\epsilon}$-insensitive in-sample loss. The forecasting gains of nonlinear techniques are associated with high macroeconomic uncertainty, financial stress and housing bubble bursts. This suggests that Machine Learning is useful for macroeconomic forecasting by mostly capturing important nonlinearities that arise in the context of uncertainty and financial frictions.

Macroeconomic Data Transformations Matter (submitted)
with Maxime Leroux, Dalibor Stevanovic and Stéphane Surprenant

From a purely predictive standpoint, rotating the predictors' matrix in a low-dimensional linear regression setup does not alter predictions. However, when the forecasting technology either uses shrinkage or is non-linear, it does. This is precisely the fabric of the machine learning (ML) macroeconomic forecasting environment. Pre-processing of the data translates to an alteration of the regularization -- explicit or implicit -- embedded in ML algorithms. We review old transformations and propose new ones, then empirically evaluate their merits in a substantial pseudo-out-sample exercise. It is found that traditional factors should almost always be included in the feature matrix and moving average rotations of the data can provide important gains for various forecasting targets.

Research Paper(s) in Progress

Identifying VARs with Transmission Mechanism Restrictions, with Maximilian Göbel

The Path to an Ice-Free Arctic: Constrained Projections of Sea Ice Area, Extent, Thickness, and Volume, with Francis X. Diebold, Glenn Rudebusch, Maximilian Göbel, and Boyuan Zhang

External Conferences/Seminars:
ML, RF, Ridge and VARCTIC refers to which paper above was (or will be) presented.

• American Economic Association (RF)	Jan 2021
• International Conference on Financial and Computational Econometrics (RF)	Dec 2020
• Bank of Italy and Federal Reserve Board Workshop on "Nontraditional Data & Statistical Learning with Applications to Macroeconomics"	Nov 2020
• Washington University Annual Economics Graduate Student Conference (RF)	Nov 2020
• Modelling with Big Data and Machine Learning, Bank of England (RF)	Nov 2020
• Vienna Workshop on Economic Forecasting (RF)	Oct 2020
• Society for Financial Econometrics, PhD Job Market Candidates seminar (RF)	Oct 2020
• Aarhus Joint Econometrics-Finance Lunch Seminar (RF)	Sept 2020
• Young Economists Symposium (RF)	Aug 2020
• Econometric Society World Congress (RF)	Aug 2020
• European Geophysical Union, Vienna (VARCTIC)	May 2020
• Modelling with Big Data and Machine Learning, Bank of England (ML)	Nov 2019
• OECD Innovation Lab, Paris (RF)	Nov 2019
• Canadian Econometric Study Group, Montreal (ML, and poster Ridge)	Oct 2019
• Forecasting at Central Banks Conference, Ottawa, (poster Ridge)	Oct 2019
• North American Summer Meeting of the Econometric Society, Seattle (ML)	June 2019
• Bank of Canada Brownbag Seminar, Ottawa (Ridge)	June 2019
• 10th Nordic Econometric Meeting, Stockholm (Ridge)	May 2019
• Workshop on High-Dimensional Time Series in Macro, Vienna (Ridge, ML)	May 2019
• Société Canadienne de Sciences Économiques, Québec City (Ridge)	May 2019
• Symposium of the Society for Nonlinear Dynamics & Econometrics, Dallas (Ridge)	March 2019
• Canadian Economic Association, Montreal (ML)	June 2018

Referee:
Review of Economics and Statistics, International Journal of Forecasting

Honors, Scholarships, and Fellowships:
- Richard T. Baillie prize in Time Series Modeling for *TVPs as Ridge Regressions*, Annual Symposium of the Society for Nonlinear Dynamics Econometrics (March 2019)
- Doctoral Scholarship, Canadian Social Sciences and Humanities Research Council (2018-2020)
- Penn Fellowship (2016-2021)