Deep Vector Autoregression for Macroeconomic Data

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Can we leverage the power of deep learning in VAR models?

We propose Deep VAR: a novel approach towards VAR that leverages the power of deep learning in order to model non-linear relationships. By modelling each **equation of the VAR system as a deep neural network**, our proposed extension outperforms modern benchmarks in terms of in-sample fit, out-of- sample fit and point forecasting accuracy. In particular, we find that the Deep VAR is able to **better capture the structural economic changes** during periods of uncertainty and recession. By staying **methodologically as close as possible to the original benchmark**, we hope that our approach is more likely to find acceptance in the economics domain.

Key contributions

- Simple methodology close in spirit to conventional benchmark
- Significant improvement in predictive performance
- Open source R package to facilitate reproducibility

Less is more

A simple methodology

We developed our idea under the following premise: **maximise performance** of an existing and trusted framework under **minimal intervention**. VAR has become a standard tool for practitioners to construct economic forecasts, but the assumption of linearity through time and variables is restrictive. We relax that assumption through one simple step: estimate each system equation through a recurrent neural network.

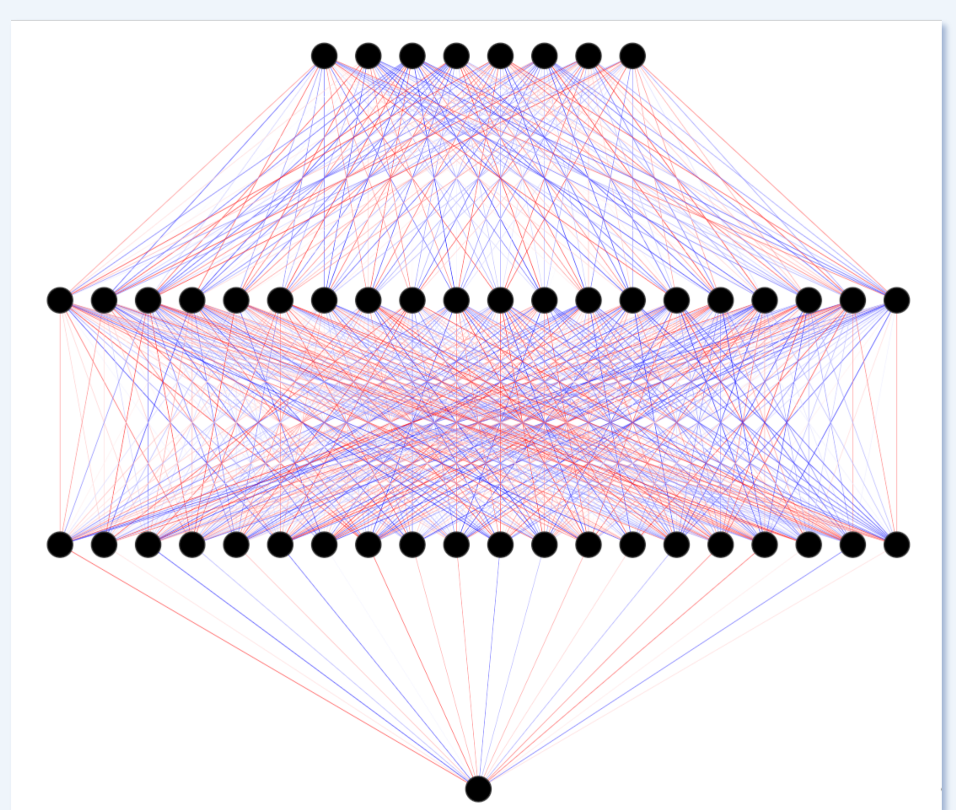

Figure 1: Neural Network Architecture. Inputs are lags of all variables. Output is variable of interest in time *t*.

Significant performance gains

Empirical evidence

To evaluate our proposed methodology empirically we use the **FRED-MD data base to collect a sample of monthly US data** on output (IP), unemployment (UR), inflation (CPI) and interest rates (FFR). Our sample spans the period from January 1959 through March 2021.

Our findings show a **consistent and significant improvement in predictive performance**: the Deep VAR incurs much lower loss than the conventional benchmark. It also outperforms other popular approaches that address non-linearity (Threshold VAR and Random Forest).

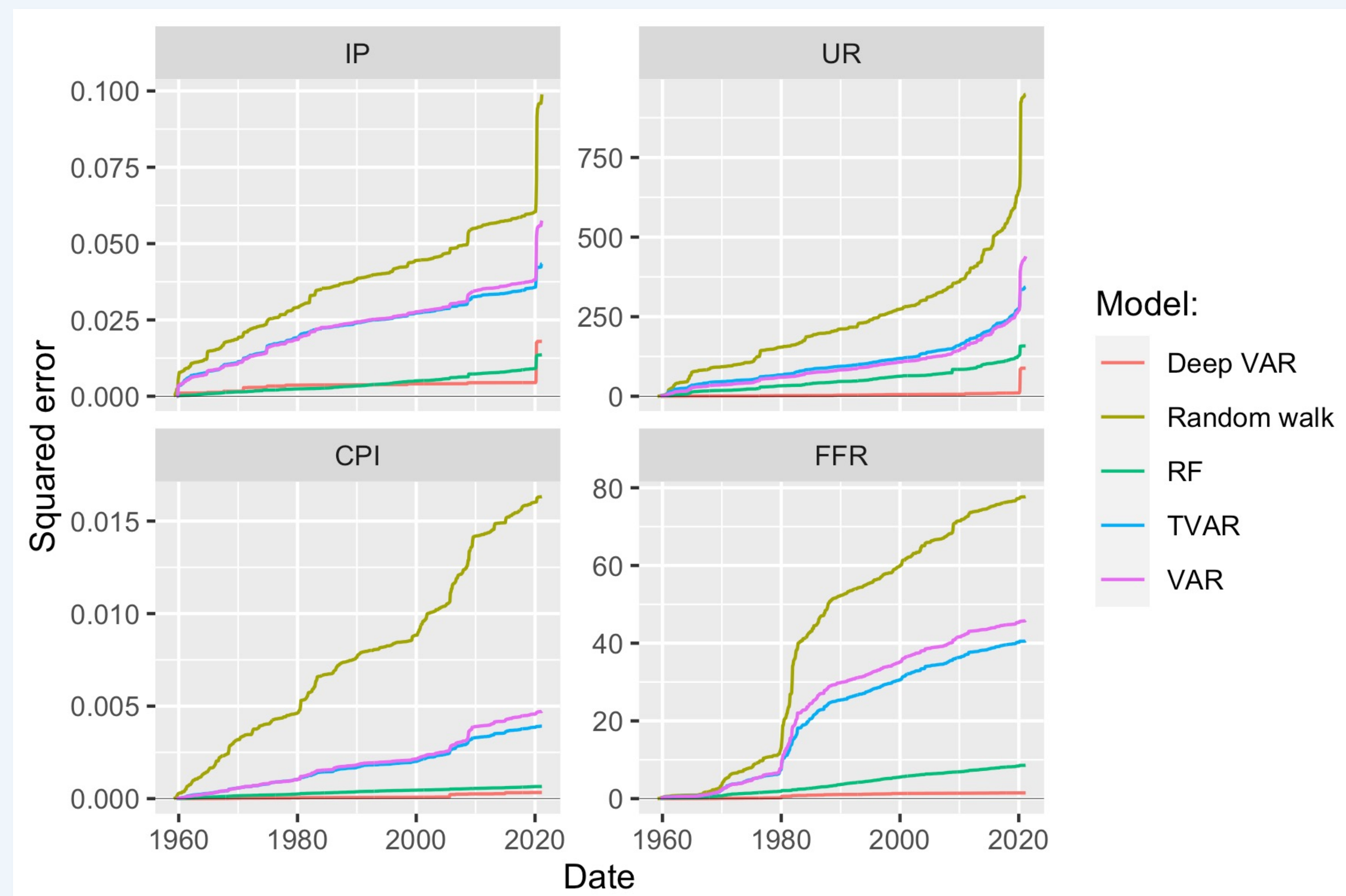

Figure 2: Comparison of cumulative loss over the entire sample period for Deep VAR and benchmarks.

We also test model performance with respect to a test sample: future realizations arrive and we compute 1-step ahead predictions without retraining (Table 1). In the paper, we also present evidence that the Deep VAR outperforms on *n*-step ahead forecasts.

Variable	DVAR	VAR	Ratio (DVAR / VAR)
IP	0.00494	0.01484	0.33253
UR	0.94542	1.65170	0.57240
CPI	0.00231	0.00342	0.67642
FFR	0.17494	0.23974	0.72972

Table 1: Test root mean squared error (RMSE) for the two models across variables.

Have we merely scratched the surface?

Hyperparameter tuning

For a our baseline comparison we keep things simple: for example, we let the conventional VAR guide our search for optimal lag length. A short exercise in hyperparameter tuning demonstrates that the Deep VAR is less prone to overfitting with respect to the number of lags among other things.

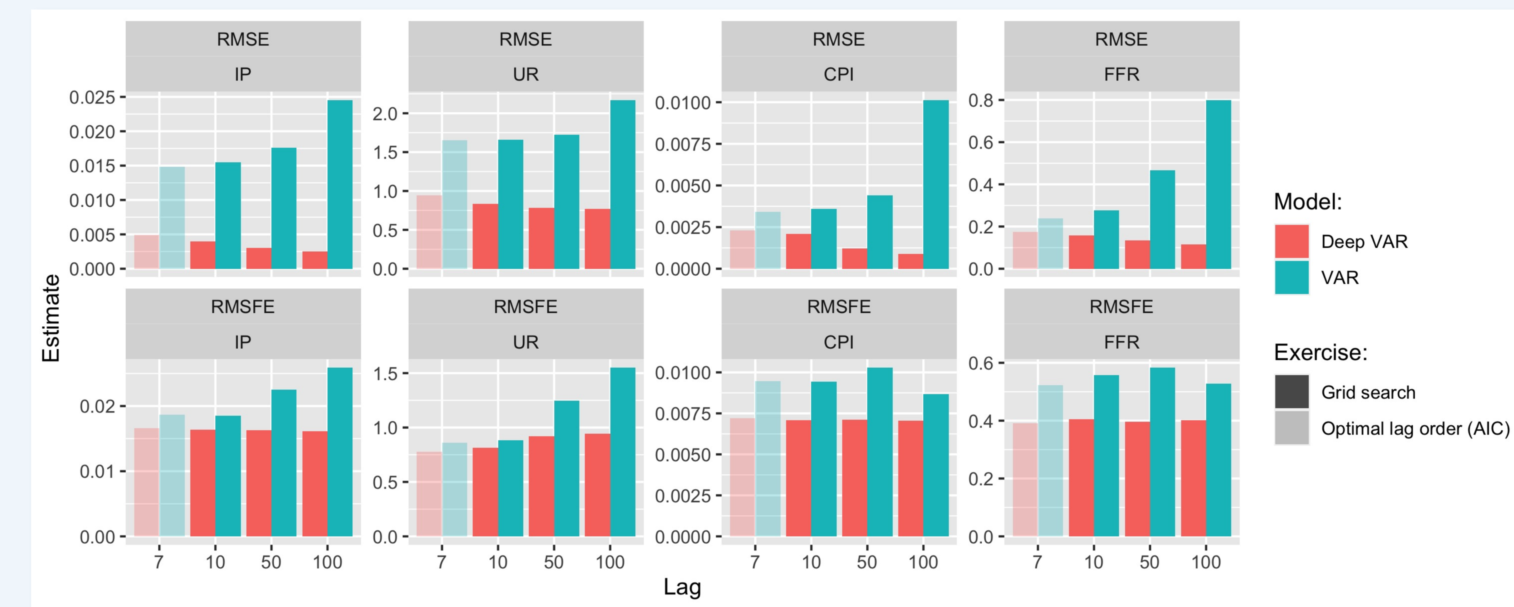

Figure 3: Pseudo out-of-sample RMSE and RMSFE for VAR and Deep VAR across different lag choices.

Where to go from here

Recent work

- Progress on **uncertainty quantification** through Bayesian deep learning – MC dropout (Gal and Ghahramani 2016).
- Recent work by Daxberger et al. (2021) shows that Laplace Approximation is a promising way forward.

Open questions

- What **other benchmark models** should we consider?
- **Structural identification** – how to proceed? Verstyuk (2020) works with Cholesky decomposition as in conventional VAR.
- Can the existing toolbox (IRFs, variance decomposition, policy counterfactuals, …) be derived for Deep VAR?
- Deep VAR as a **tool for detecting non-linearities**?

References

Daxberger et al. (2021). "Laplace Redux-Effortless Bayesian Deep Learning.". In: Advances in Neural Information Processing Systems 34

Gal and Gaharamani (2016). "Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning.". In: International Conference on Machine Learning, 1050–59. PMLR.

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