Neural Networks for Macroeconomic Forecasting

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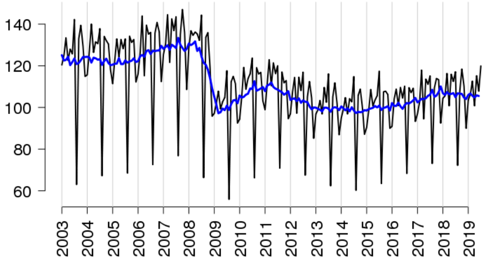
Motivation

- High frequency macroeconomic indicators provide early pictures of the ongoing state of the economic activity
- However, time-lag imposed by delayed release of official statistics undermines their power, E.g. as forecasting tools
- Short-term predictions (before the official release) of macroeconomic variables is essential for a central bank in order to enhance better policy decisions, given their relevance on the economic activity

The Industrial Production Index



- Monthly indicator measuring the volume of a country's industrial production, relative to a base year
- Strong seasonality, with cyclical fluctuations around an upward trend
- Relevant to explain aggregate fluctuations and to detect business cycle turning points
- Key forecasting tool for short-term evolution of GDP of many industrialized countries (Bovi et al. 2000, Golinelli and Parigi 2007)

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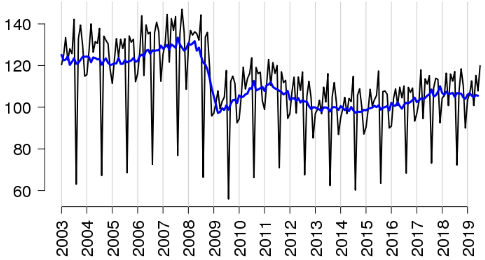

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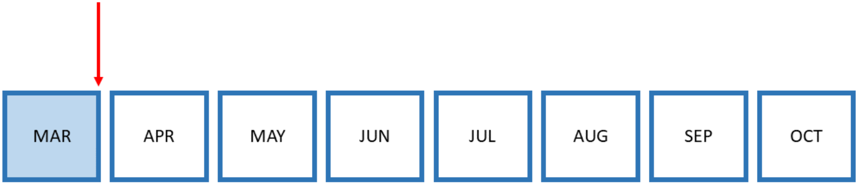
- Released in Italy by ISTAT with 45 days delay

Setup



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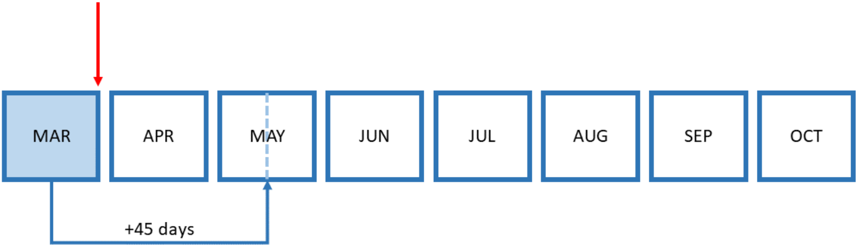

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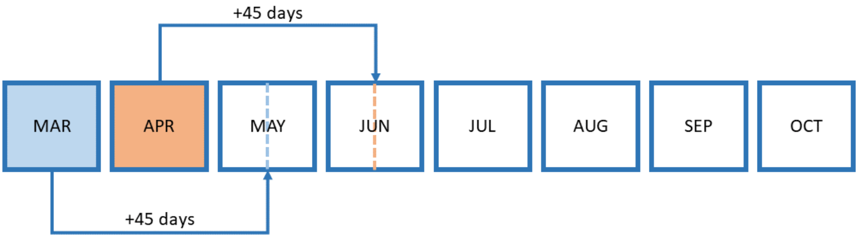
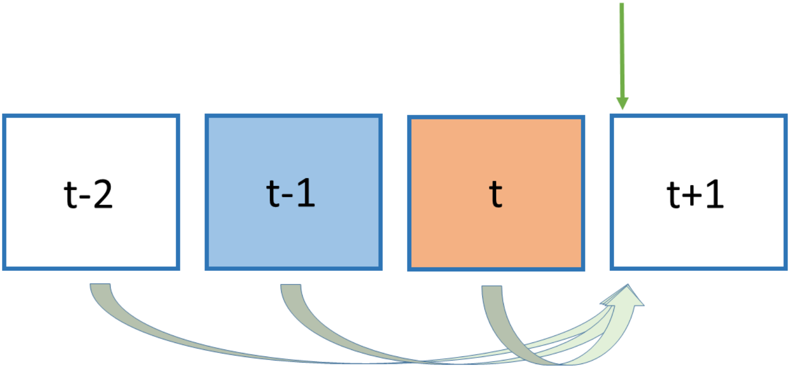


Setup

Predictions before official release of an indicator as *short-term* forecasts.
Let y_t be the value of target variable Y at current time t,

- Forecast: $\hat{y}_{t+1}$
- Nowcast: $\hat{y}_t$
- Backcast: $\hat{y}_{t-1}$



Classical models and BVARs

Classical models

- They exploit co-movement between the national electric consumption and the IPI
- Direct and indirect approach for modeling industrial production using several monthly indicators
- Predictions aggregated via model - averaging

BVARs with Minnesota type prior

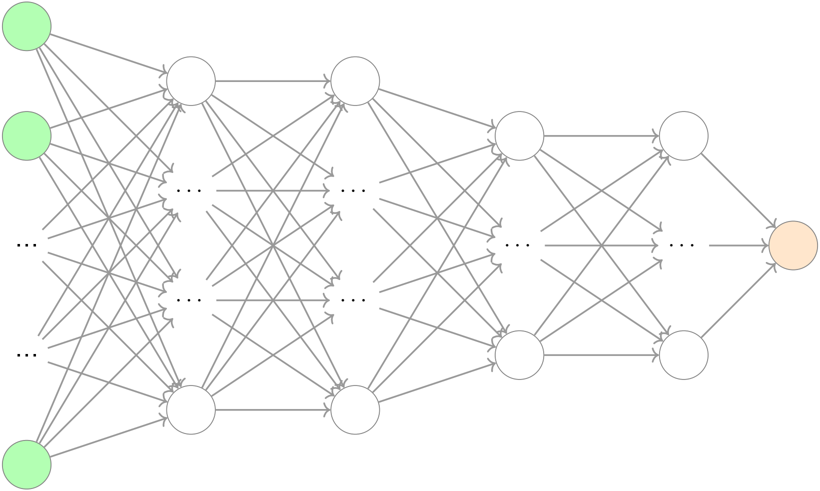
- Use larger info set with respect to classical models: GAS + Rail and Road transport flows (Shared Indicators)
- BVAR Target with Soft Indicators; Survey data, confidence indicators, PMIs
- BVAR No Soft with Hard indicators; Foreign trade stat., German new orders, Layoff funds, Business loan flows, ...

Neural Networks and Deep Learning

- From machine learning as representation rule to deep learning as sequence of representation *layers*
- Neural Networks (NN): Directed graphs whose nodes (*neurons*) are grouped into *layers* (primary building blocks)
- The way neurons are arranged into layers, the connection patterns between layers, the activation functions, and learning method define a NN's *architecture*
- Under general conditions Neural Networks are universal function approximators
- Deep Regression methods as black boxes: can be applied to model complex frameworks and provide lower error rates
- Today, state-of-the-art in computer vision, automatic translation, image recognition, etc

Feed Forward NN

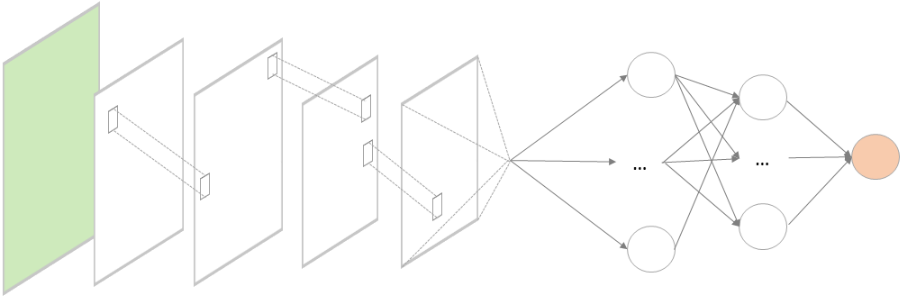
Plain Dense network architecture:



- Free hyper-parameters: Number of neurons, activation function, optimization method
- Training: Dropout + Multiple Restarts

Convolutional NN

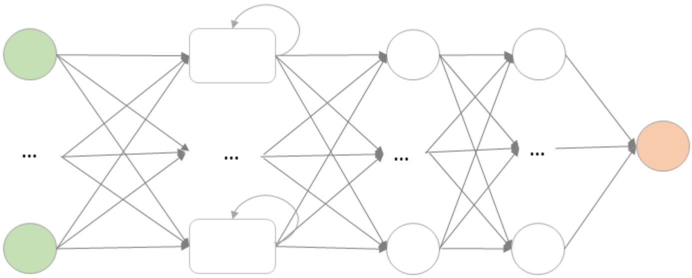
Stacking of Convolutional and Dense layers:



- Free hyper-parameters: Size of filters in Convolutional layers, Number of neurons in Dense layers, activation functions, optimization method
- Training: Dropout + Multiple Restarts

Recurrent NN

Stacking of a single Recurrent layer with LSTM units and Dense layers:

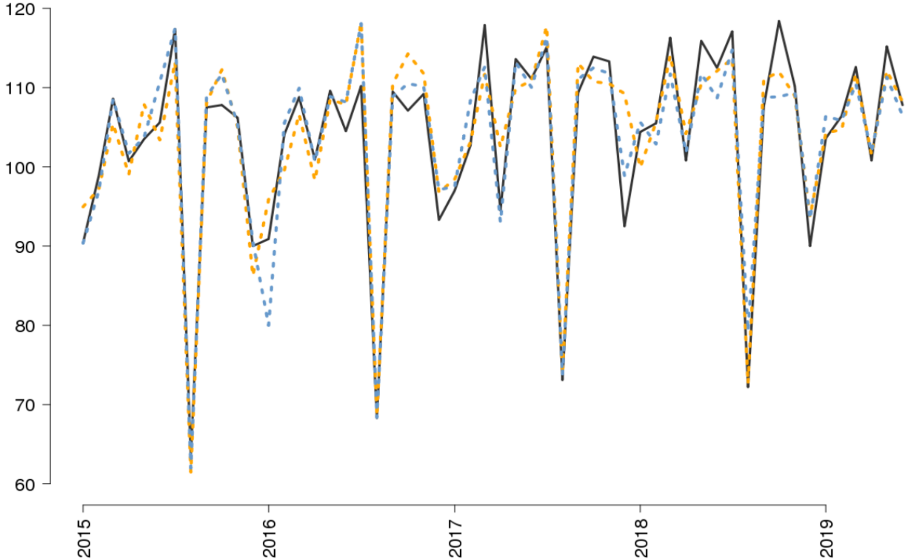


- Free hyper-parameters: Number of units in Recurrent layer, optimization method
- Training: Dropout + Multiple Restarts

Results: Raw IPI Level

	MAPE		Bias		Dir. Accuracy	
	Nowcast	Backcast	Nowcast	Backcast	Nowcast	Backcast
FF Soft 11y	0.45%	2.26%	0.53	-2.23	0.83	0.87
FF Soft 7y	0.41%	0.20 %	-0.29	-0.09	0.83	0.89
Conv Soft	0.61%	0.93%	-0.49	-0.73	0.85	0.91
Recurrent Soft	0.92%	1.46%	0.17	-0.47	0.56	0.66
FF No Soft 11y	0.10%	3.03%	-0.96	-3.17	0.89	0.91
FF No Soft 7y	0.38%	0.40%	-0.27	-0.34	0.89	0.93
Conv No Soft	1.26%	1.57%	-1.24	-1.44	0.83	0.93

Results: Plain Dense NN with 7 Years Window



Results: Seasonally Adjusted Series Growth Rate

	RMSFE		MAE		Directional accuracy	
	Nowcast	Backcast	Nowcast	Backcast	Nowcast	Backcast
FF Soft 11y	1.16	1.11	0.93	0.88	0.56	0.56
FF Soft 7y	0.82	1.13	0.68	0.94	0.56	0.39
Conv Soft	1.12	1.31	0.85	1.03	0.56	0.56
Recurrent Soft	1.44	1.70	1.15	1.23	0.41	0.51
FF No Soft 11y	1.07	1.14	0.89	0.94	0.48	0.50
FF No Soft 7y	1.06	1.13	0.84	0.89	0.50	0.50
Conv No Soft	1.22	1.16	1.02	0.94	0.48	0.50

Results: Seasonally Adjusted Series Growth Rate

	BIAS		Rel. RMSFE†		Rel. MAE†	
	Nowcast	Backcast	Nowcast	Backcast	Nowcast	Backcast
Classical model	-0.02	0.07	0.80	0.74	0.73	0.70
BVAR Soft	0.58	-0.18	1.48	0.78	1.44	0.74
FF Soft 11y	0.02	0.02	0.88	0.85	0.93	0.88
FF Soft 7y	0.01	0.03	0.62	0.87	0.68	0.94
Conv Soft	0.05	0.04	0.84	1.01	0.85	1.03
Recurrent Soft	0.07	-0.02	1.09	1.31	1.15	1.23
BVAR No Soft	0.60	-0.32	1.50	0.70	1.47	0.71
FF No Soft 11y	0.05	0.03	0.81	0.88	0.89	0.94
FF No Soft 7y	0.02	0.02	0.80	0.87	0.84	0.89
Conv No Soft	0.02	0.00	0.92	0.89	1.02	0.94

† RMSFE and MAE are relative to a simple benchmark based on seasonality
Forecasts from NNs in pseudo-real time, Traditional models in real-time

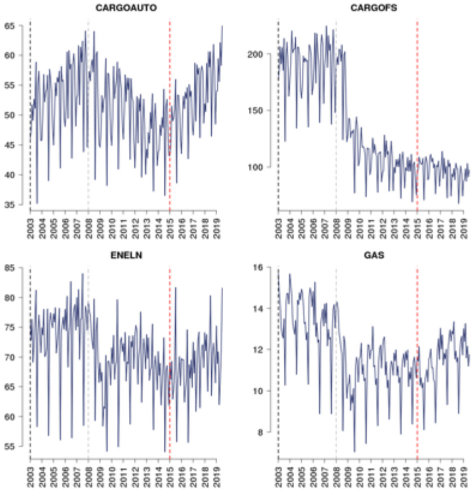
Final Remarks

- We compared point estimates from different models over 54 months (from Jan 2015 to June 2019) and found comparable forecasting accuracy
- Neural networks proved able to capture hidden pattern in data when information is incomplete (nowcast)
- However, traditional statistical models were fairly accurate with complete information (backcast)
- Neural networks as *black boxes*: while capturing complex behaviour, interpretability is an issue
- What next?
  - From Pseudo-real time vs real time to plain real time
  - From point estimates to intervals
  - Bridge Neural Networks and Traditional models to improve overall forecasting accuracy?

Q & A

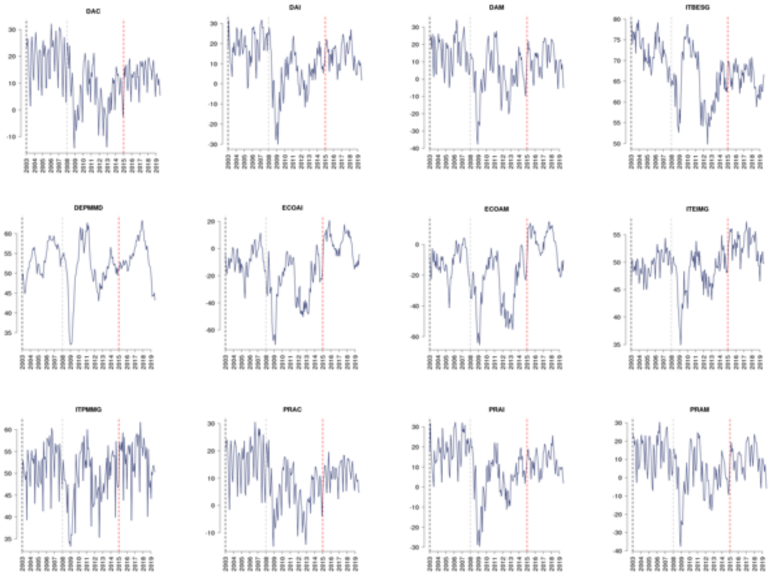
Data: Shared Indicators

Strongly related indicators on energy consumption (real-time) and transport of goods (lag-1)



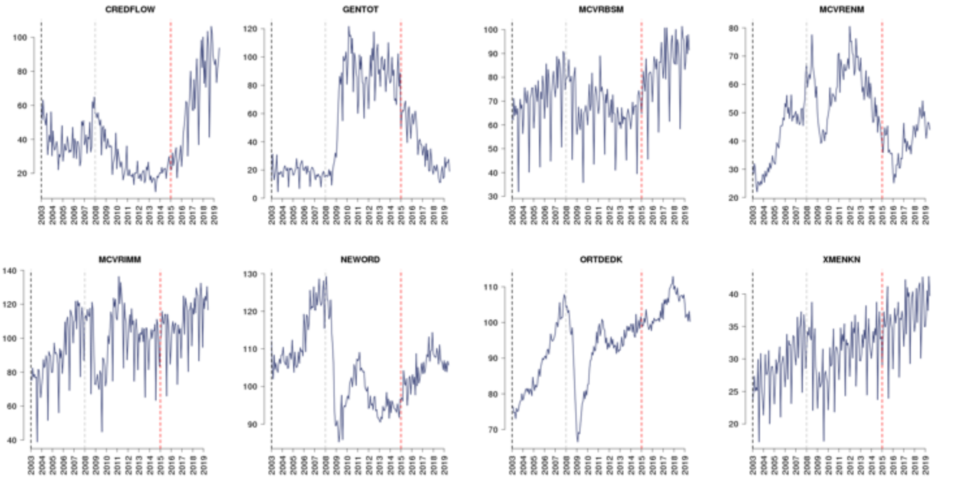
Data: Soft Indicators

Real-Time Monthly business tendency survey data



Data: Hard Indicators

Last available economic Indicators, up to lag-2



Neural Networks and Deep Learning

- Dense: Linear combination of weights ($\mathrm{W}:_h \in \mathbb{R}^{n_h \times n_{h-1}}$) and biases ($\mathrm{b}_h \in \mathbb{R}^{n_h}$) with input ($\mathrm{Z}_{h-1} \in \mathbb{R}^{n_{h-1}}$) via an activation function (f_h):

$$\mathrm{Z}_h = f_h\left(\mathrm{W}_h \mathrm{Z}_{h-1} + \mathrm{b}_h\right) \quad h = 0, \ldots, H$$

- Convolutional: Input is filtered and mapped into matrices. These are combined by a further Pooling layer
- Recurrent Layer with LSTM units: Maps a time-series combining input at time t and its L internal units' state at time $(t-1)$. Each unit trains 4 distinct matrices of weights

- *With great power* (complex parametrization) *comes great responsibility* (many data points required for reliable training)
  - $\rightarrow$ Hyper-parameters tuning with k-fold Cross-Validation
  - $\rightarrow$ Dropout while training + Multiple Restarts