Predicting Inflation with Neural Networks
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Highlights
- This paper applies neural networks to predict US CPI inflation, and in particular a recurrent neural network
- Neural nets present better performance than usual benchmarks, especially at the one and two-year forecast
- Recurrent neural nets are at least as good as the traditional feed forward neural net at medium-long horizons
- Macroeconomic information is important during periods of high uncertainty
- The paper also addresses the impact of the stochastic initialization of parameters on forecasting performance

Econometric framework
Consider two sets of predictive variables:

\[ \mathbf{x}_t = (x_{1t}, \ldots, x_{Nt})' \]: pool of economic predictors

\[ \mathbf{y}_t = (y_{1t}, \ldots, y_{Mt})' \]: CPI and its components

Let \( \mathbf{z}_L^t \) be the set collecting the current and lagged values of \( \mathbf{z}_t = \mathbf{x}_t, \mathbf{y}_t \) or \( (\mathbf{x}_t, \mathbf{y}_t) \)

I suppose that inflation, \( y_t \in \mathbb{R} \), evolves nonlinearly with respect to \( z_L^t \) through a function \( G \):

\[ y_{t+h} = G(z_L^t; \Theta_h) + \epsilon_{t+h} \]

Fitting the unknown function \( G : z_L^t \rightarrow y_{t+h} \) to the data corresponds to estimating \( \Theta_h \) given a network architecture, \( \mathcal{A}_h \), by minimizing

\[ L = \frac{1}{T} \sum_{t=1}^{T} \left( y_{t+h} - G(z_L^t; \Theta_h) \right)^2 \]

- \( \mathcal{A}_h \): neural net model & tuning parameters
- Universal approximation theorem (Cybenko, 1989): simple neural net model can approximate any continuous function up to an arbitrary degree of accuracy

Out-of-sample performance

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RMSE Loss ratios with AR(1)

References