Nowcasting methodologies

Advances and practical resources

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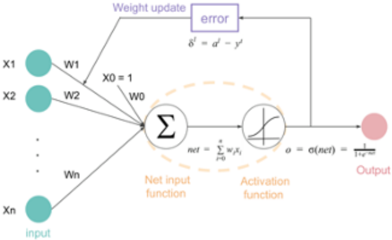
Artificial neural networks (ANNs)

- Networks of layers and nodes (neurons) that transform input data using weights to obtain an output
- Outputs are run through non-linear activation function (often ReLU), plugged into cost function, weights are updated using gradient descent, process repeated

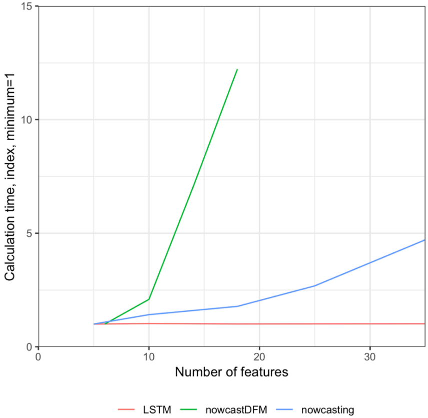


Long short-term memory networks (LSTM)

- Traditional feed-forward ANNs don't have a time component, usually work with many independent observations (e.g. photos)
- Recurrent neural networks (RNNs) introduce temporal aspects to ANNs, but suffer from "vanishing gradients" and a "short" memory
- LSTMs mitigate the problem by introducing "forget gates", allowing gradients to flow unchanged through the network
- Primarily used in natural language processing (NLP), video data, etc.

LSTMs and nowcasting data problems

- Can handle mixed frequency data, able to learn complex, non-linear relationships between variables
- Ragged edges can be filled with various methods, e.g. the mean,ARMA models, etc.
- Can handle huge numbers of input variables due to efficiency and separate the signal from the noise itself

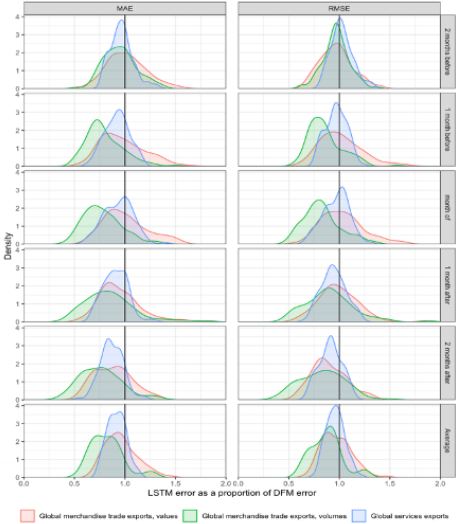


Comparison with dynamic factor models

- First UNCTAD research paper
- An empirical analysis was carried out comparing LSTMs to DFMs
- 3 target variables, global merchandise trade (values and volumes), global services trade
- Large pool of over 100 potential explanatory variables (both monthly and quarterly series)
- Training period from Q2 2005 Q3 2016
- Test period from Q4 2016 to Q4 2019
- 100 random sample of variables, tested on both LSTM and DFM (for robustness, either method could be better by chance on a given dataset)

Results

Figure 2. LSTM error as a proportion of DFM error



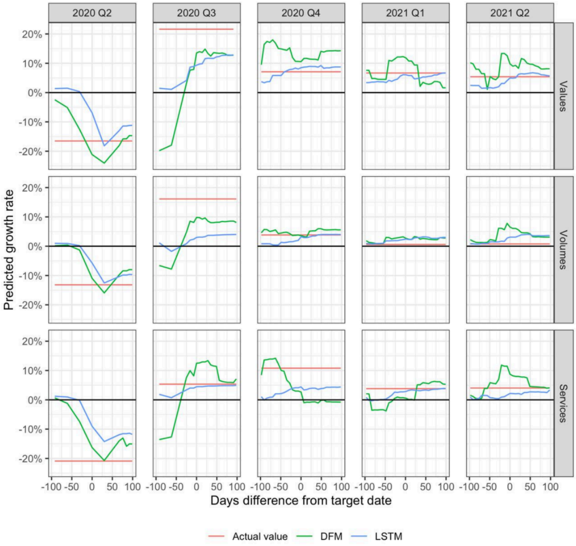
Takeaways

- Pros:
  - LSTMs can handle many more input variables than DFMs while still getting good predictions
  - Can be trained on any dataset,DFM sometimes throws errors for non-invertible matrices
  - More flexibility regarding mixed-frequency inputs, can theoretically handle daily data together with yearly. DFM internals need to be reworked to handle another frequency
- Cons:
  - Stochastic nature of ANNs and LSTMs, two models trained on the same data give two different predictions. Can be mitigated by training many models and taking the average, median, or using more complex ensembling methodologies
  - Lack of interpretability in parameters, lack of inference to what's driving changes (no longer true since version 0.2.0 of *nowcast_lstm* library)

Comparison with dynamic factor models (cont.)

- Second UNCTAD research paper specifically evaluating performance during COVID crisis
- Again comparing LSTMs to DFMs
- Same 3 target variables, global merchandise trade (values and volumes), global services trade
- Same input variables for both models; originally chosen because of good performance with the DFM
- Test period from Q2 2020 to Q2 2021

Results


2020 Q2
2020 Q3
2020 Q4
2021 Q1
2021 Q2
Values
Volumes
Services
Predicted growth rate
20%
10%
0%
-10%
-20%
-100 -50 0 50 100
Days difference from target date
Actual value
DFM
LSTM

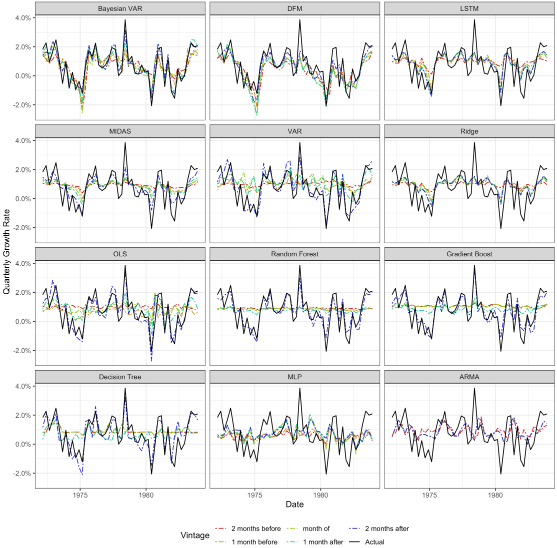
Takeaways

- LSTM predictions seems to start off more conservatively
- Don't vary as much over time, smaller adjustments, gradual development
- Seems more monotonic than DFM, don't see shifts in direction or narrative as often
- DFM very much influenced by most recent observed value
- LSTM rarely if ever has a major adjustment not reflected by the DFM, inverse happens very often
- In all quarters for all variables, DFM has bigger adjustments than the LSTM more often than vice versa, sometimes dramatically so
- Implications for forecasting and decision-making: LSTM appears better suited than DFM. Early forecasts should be more conservative, gives the model more time and slack to build confidence in a prediction, gives consistent narrative without need for extreme adjustments.

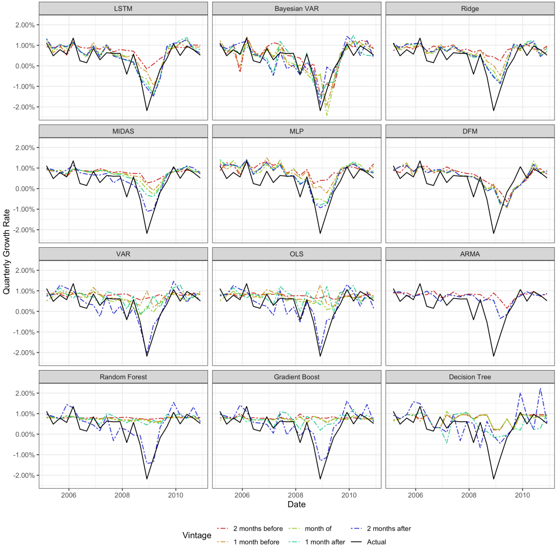
Comprehensive benchmark analysis

- Third UNCTAD research paper evaluating all common nowcasting methodologies plus some machine learning methodologies
- Target variable of US quarterly GDP growth
- Input variables from Bok et al. 2018
- 3 test periods covering volatile times in US economic history: early 1980s recession, 2008 financial crisis, COVID crisis

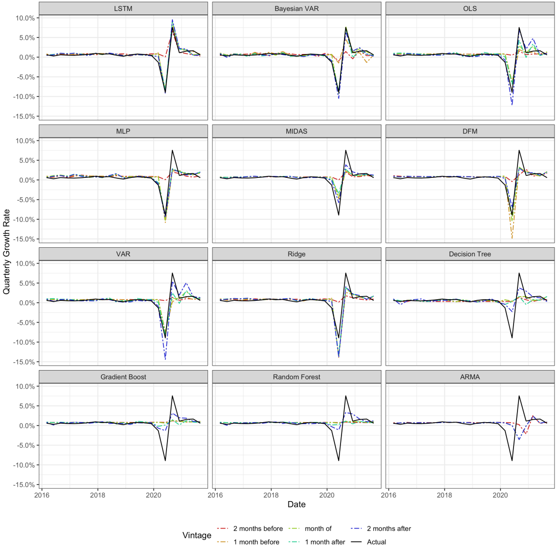
Results: early 1980s recession



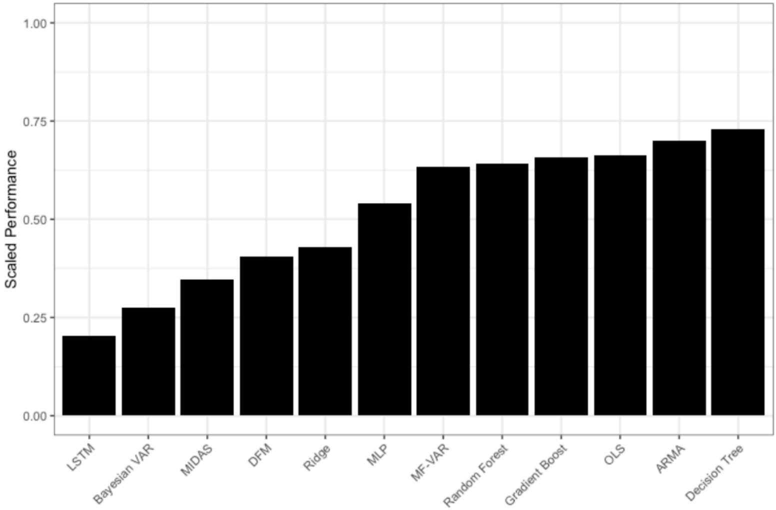
Results: 2008 financial crisis



Results: COVID crisis



Results: overall



Takeaways

- Best performing methodologies were LSTM and Bayesian VAR
- MIDAS and DFM also solid performers
- Bayesian VAR suffers from high volatility

nowcast_lstm multi-language library

- Alongside first paper, developed Python library to enable general use of LSTMs for economic nowcasting
- Also contains other helpful nowcasting analysis-specific functionality, such as testing on artificial lags, and example files
- Available in Python, R, MATLAB, and Julia.

Benchmark analysis repository

- Alongside third paper, set up open-source repository with boilerplate code for each methodology
- Access to a standalone notebook where backing data can be changed to run analyses with chosen methodology on new data
- Available on GitHub

Conclusion

- LSTM is a flexible, powerful methodology well-suited to economic nowcasting
- Its performance has been validated in several empirical studies and is made accessible and easy to try with the libraries
- Other nowcasting methodologies are also made more accessible with the benchmarking repository and accompanying paper
- For any common nowcasting methodology, practitioners can obtain context, see model performance, and adapt the code for their own applications

Resources

- First UNCTAD research paper
- Second UNCTAD research paper
- Benchmark UNCTAD research paper
- LSTM library
- Benchmark repository