Deep Learning and Finance: Here We Go Again

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Abstract
The emergence of open-source Deep Learning (DL) tools such Google's TensorFlow and Apache's MXNet have made the application of DL as easy as closed-sourced tools made regression 40 years ago. Given DL's tremendous success in a variety of applications, it is no surprise to see it being touted as the next big thing in empirical finance. The notion of using DL in finance, however, is not new. A leading textbook in financial econometrics, copy-written in 1997, proposes the use of the multi-layered perceptron and parallel processing. There are also several books from a decade ago on the use of neural networks in finance. Using two workhorse empirical models in finance and standard Monte Carlo methods, we show in our use cases that DL performs no better on test sets (out of sample) than simple regression. In contrast, they consume considerable computing power, even with the most sophisticated architectures currently available.

Summary

Economics and finance have "workhorse" empirical models used to examine hypotheses derived from theory. In labor economics, there is the Mincerian wage function. In finance, there are the capital asset pricing model (CAPM) and the Fama-French x-factor model (FFXF). These models are so ubiquitous that references are unnecessary. As an empirical application, the neural network, first proposed before these workhorse models, is a nonlinear statistical model.[1] It is now standard to refer to adaptations of this approach as deep learning (DL), and the emergence of open-source DL tools such Google's TensorFlow and Apache's MXNet have made their application as easy as closed-sourced tools made regression 40 years ago. Moreover, they have long appealed to empirical finance for their potential to uncover—and to profit from—sophisticated correlation patterns. Indeed, a leading textbook in financial econometrics, first copy-written in 1997, proposes the use of the multi-layered perceptron (MLP), a simple neural network.[2] There are also several books from a decade ago on the use of neural networks in finance.[3]

Table 1: CAPM with AAPL Daily Returns

Model	Run Time[1]	Average MSE[2]	Smallest MSE[2]
OLS	0.009	0.264	0.209
MLP	8.557	0.274	0.217
LSTM[3]	12.170	0.436	0.355
LSTM[4]	19.064	0.384	0.304

1: Average seconds per replication
2: 10^{-3}
3: 30-day window
4: 90-day window

Table 2: FF5F with AMZN Daily Returns

Model	Run Time[1]	Average MSE[2]	Smallest MSE[2]
OLS	0.024	0.109	0.099
MLP	13.424	0.111	0.100
LSTM[3]	14.093	0.142	0.128
LSTM[4]	22.236	0.133	0.116

1: Average seconds per replication
2: 10^{-2}
3: 30-day window
4: 90-day window

Using these workhorse finance models, we examine the performance of DL using a large-scale MLP and a recurrent neural network (RNN or its time-series equivalent, LSTM). Using standard Monte Carlo methods, we benchmark their performance against linear regression (OLS). Table 1 displays results for CAPM using Apple's daily returns (AAPL), and Table 2 displays results for FF5F using Amazon's daily returns (AMZN). We find that neither DL approaches perform better than OLS using the mean-squared error (MSE) criterion, a standard measure of forecast performance. They do, however, come with considerable computational expense—even using a sophisticated computing architecture.[4]

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1 Hastie, *et al.*, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition, Springer, p.392.

2 Campbell, *et al*., The Econometrics of Financial Markets, Princeton University Press, p.515.

3 See, *e.g.*, McNeils, Neural Networks in Finance, Elsevier Academic Press, 2004.

4 16 machines, each with 64 cores and 256GB of RAM.