Deep Recurrent Factor Models

Literature Review

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Introduction

In quantitative finance prediction of stock returns is an important sphere of research. It is of interest for multiple participants in the financial market to accurately predict future returns, i.e. increase or decrease in market value of a given publicly traded company. Industry practitioners such as portfolio/risk managers use statistical models to predict stock returns to support their respective decision making processes.

One of the most common approaches to predict future stock returns is to model stock returns by means of a linear model, where independent variables are ought to explain stock price variability. In such a model the predictor variables are referred to as 'factors'. Fama and French [1993] introduced the highly influential 3-factor model which tries to explain returns of stocks with the following factors:

- beta (returns in excess of the market),
- size (market capitalization),
- value (price-to-earnings ratio).

One should note that there are many potential factors. Researchers have identified over 300 such factors in the past (Harvey et al. [2016]).

Factor models assume a linear relationship between stock returns and factors, which is not always accurate. Researchers have used deep learning in the past in an effort to make better predictions on stock returns (e.g. Krauss et al. [2017], Bao et al. [2017]). The practical problem in using deep neural networks for the purpose of prediction lies in the fact that deep neural networks are often hard to interpret. Since the relation between input and output variables is not always clear, it will often not be considered in practice, seeing that portfolio managers, who manage large amounts of customers funds, are generally hesitant to assume models where the direct influence of explanatory variables cannot be easily explained to other stakeholders. Deep learning models are therefore often considered to be 'black-box' tools and linear models are used instead.

The assumption of a linear relationship between returns and factors is often challenged, e.g. by Dittmar [2002] or Levin [1995], as there is evidence that non-linear models might be a better choice for predicting stock returns. [Nakagawa et al., 2019] use a deep learning model to model the non-linear relationship between factors and returns of Japanese stocks. The authors use a deep long-short-term memory network (LSTM) to predict future returns of stocks traded on the Japanese stock market and show that their model has better predictive capabilities than the traditional linear models. In addition, [Nakagawa et al., 2019] consider the time-varying effect of factors onto stock returns, by choosing a LSTM over a conventional deep neural network.

[Nakagawa et al., 2019] solve the interpretability problem associated with deep neural networks by utilising layer-wise relevance propagation (LRP), a technique which provides explainability to complex deep neural networks. The general approach of LRP is outlined by Montavon et al. [2019] and a variation that is applicable to LSTM networks is presented by Arras et al. [2017].

Research Question

We would like to implement and apply the approach used in [Nakagawa et al., 2019] to model the returns of stocks traded on the US stock market and verify that non-linear factor models similarly outperform the predominantly used linear factor models on the US stock market.

Methodology and Data

- We will fit a LSTM model to the data provided by Chen and Zimmermann [Forthcoming], a collection of monthly returns of portfolios representing over 300 different factors based on stocks traded on major US stock exchanges.
- We will fit the model to the return time series of the constituents of the SP500 stock index, which is often considered a representative index for the US stock market.
- Consistent with [Nakagawa et al., 2019], we will fit the model based on the data from December 1990 to March 2015. We will try to use the same factors as were used by [Nakagawa et al., 2019]. We will use the same period as [Nakagawa et al., 2019] for train, validation and test sets.
- We will conduct LRP after fitting the model and interpret the relevance scores for each input factor.
- We will compare the prediction performance with the corresponding linear model.
- The code necessary for the task will be written in `Python 3`.
- The LSTM model will be fit by means of the `Keras` library.

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