Project Proposal Deep Learning Fall 2018

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Our project topic is predicting stock prices using a novel deep learning feature-selection approach. The input variables are stock prices, volumes, stock symbols and derived indicators. Response variable (target variable) is a per asset return for the next day (weekends count as one day). Loss function is:

$$L = \sum_{t=1}^{n} r_{t+1} * 1_{\hat{r}_{t+1} > \theta} - r_{t+1} * 1_{\hat{r}_{t+1} < -\theta}$$

where $r_{t+1}$is our target variable, $\hat{r}_{t+1}$ our prediction, θ is a threshold (hyperparameter), indicating, when to take a position. The above loss function measures the profit and loss, when taking a position whenever the prediction exceeds the threshold θ.

I. Data

We use the following data set [9]. Market data per asset (1/1962 to 1/2017) for all US stocks. Market data are open, high, low, close and volume. Prices are adjusted for splits and dividends.

II. Literature Review

A good literature review over the use of machine learning techniques in the financial is given in "Computational Intelligence and Financial Markets: A Survey and Future Directions"[3]. This paper also covers deep learning techniques as part of machine learning. It states that, the application of deep leaning methods to the field of financial forecasting remains a relatively unexplored area.
One of the novel methods that we will investigate is using an algorithms used to predict earthquakes to decide whether certain features are significant or not, which was also used for stock prediction. We will investigate to what extent this improves the performance of the deep neural network. Previous work is given by: [2], [1]

We will also review published code in [6] and the published discussion in [7].

III. Implementation of existing methods

The starting point of our implementation is the following neural net baseline implementation adapted to our problem: [8]. This implementation has the following characteristics:

1) We predict the return of the respective stock for the next day. The implementation will be in Python using Tensorflow (plus other packages).
2) Loss function: As defined above.
3) No feature engineering.
4) The baseline neural net is used for predicting different stocks. This is done by embedding the individual assets in an embedding space, similar to word embeddings.

This implementation should help us to better understand the strength and weaknesses of this approach.

IV. Improvements of existing models

We want to improve the baseline implementation in the following directions

1) Mutual dependencies of assets. The embedding of different stock symbols in an embedding space is novel and innovative. One neural net for predicting several underlyings.
2) We want to use the recent past to predict the near future. This has also been shown in [4].
3) Feature engineering:
   We will not use technical indicators like all forms of moving averages, price oscillator indicators or relative strength indicators that have been used in the financial industries for centuries.
   Instead, we will 1. investigate a novel method by using an algorithms that is usually used to predict the significance of an earthquake happening. 2. investigate on methods used in Bayes net to filter out dependencies between indicators and target variable.
4) We will analyze the effect of restricting to relevant feature on the deep neural net performance.

References

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[4] Christopher Krauss, Xuan Anh Do, Nicolas Huck *LaTeX: Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500*
[5] Omer Berat Sezer, Ahmet Murat Ozbayoglua *LaTeX: Algorithmic Financial Trading with Deep Convolutional NeuralNetworks: Time Series to Image Conversion Approach*
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[9] Kaggle, https://www.kaggle.com/borismarjanovic/price-volume-data-for-all-us-stocks-etfsdataset, set, viewed 12 Dec. 2018