

Deep Learning Architectures

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I. ABSTRACT

Irgendein Abstract... zusammenfassend VII.

II. INTRODUCTION

Neural networks experienced a steep rise in popularity over the last years. One reason for this trend is the versatility of these networks. They are being deployed in many domains such as computer vision and pattern recognition, predictions, robotics and self-driving cars and many more.

However, quite few scientific papers of neural networks are released in the financial domain with the objective to predict the development of stock prices. The task of stock course prediction is difficult as the stock prices are influenced by a multitude of seemingly unpredictable and uncorrelated factors. Nevertheless, the development of a stock course depends strongly on the actions of traders. Those traders could use the search engine google to gather information about stocks they are interested in right before a trade. The service *Google Trends* views various graphs displaying data of search terms typed in by users at the google search engine. This service is accessible by the public. Based on these thoughts the following hypothesis can be formulated:

A correlation between google trends search terms and stock courses exists.

In this paper the previous hypothesis is being investigated. In order to check the existence of a correlation between google trends data and stock courses, a neural network will be implemented and verified.

TODO: bei den related work papern schauen, ob hier material für weiteres zum Intro passen würde!!!

III. RELATED WORK

+ stock market description: chaotic, volatile, complex and seemingly unpredictable + result: few research teams try to find a way to predict stock development + the hype of deep learning also triggered the research in the field of stock market prediction, as dl models find application in a huge variety of domains (so why not prediction of stock prices) + however: older research only hit about 5% accuracy at best, even more discouraging for future work + nevertheless: recent research work used the improving methods of dl by using RNN and RBFNN and therefore the accuracy was improved

As a result of the stock market being chaotic, complex and volatile, there are few published research papers to facilitate the work for this paper.

Nevertheless, the few scientific papers exists which try to predict stock market development.

There are few published research papers in the fields of deep learning and neural networks regarding the prediction of price development. Additionally, most of the available research's results are discouraging. The accuracy of price prediction is quite low with about 5%.

Although the number of publications are few, the

In Singh and Srivastava (2017) the authors use a combination of (2D)2PCA + Deep Neural Network (DNN) and compare this model with the current state of the art (2D)2PCA + RBFNN.

In Chong and Park (2017) the authors have done some shit.

IV. BASIC IDEA

google trends to stocks

V. BACKGROUND

lstm, rnn

VI. DATASETS

There are many databases, which provide a lot of datasets. One of those is *kaggle*. *kaggle* does not only provide datasets, they also organize competitions in analyzing datasets or improving already invented algorithms. We found a lot of data about to *New York Stock Exchange*. Unfortunately we did not find one single dataset which satisfied all our requirements. There was no data about how often a search term was requested at *Google*. So we had to collect the data ourselves from *Google Trends*. In the following chapters we describe our datasets and why we are using them.

A. Stock data

We combined data about the *New York Stock Exchange* of two datasets from *kaggle*.

1) *NYSE*: Gawlik (2017) collected information about historical prices of the S&P 500 companies and additional fundamental data in his dataset. Standard and Poor's 500 (S&P 500) is a stock index of the 500 biggest US companies listed on the stock exchange.

The dataset has 4 files:

- **prices.csv** This file contains the daily stock prices from 2010 until the end of 2016. For newer companies the range is shorter. Unfortunately the prices are sorted by day and not stock and therefore we could not use this data without preprocessing it. Instead, we found a better suiting dataset.
- **prices-split-adjusted.csv** Approximately 140 stock splits occurred during that time. This file has the same data with adjustments for the splits. We do not use this data neither.

- **fundamentals.csv** The file summarizes some metrics from the annual SECC 10K fillings. The metrics are useless for us, too.
- **securities.csv** Additional information for each stock can be found in this file. The most important data is the mapping from the ticker symbol to the full name of the companies. We use this data as an input for collecting data from *Google Trends*.

2) *S&P500*: The second dataset from *kaggle* has also information about the daily stock prices from the S&P 500. Nugent (2017) ordered the prices by stock and are therefore much more useful for us. Each entry consists of the date, four prices, the volume and its ticker symbol. The dataset has the prices for the last five years starting at 2012-08-13 until 2017-08-11. For the weekends there are no entries because the stock market is closed and no trading happens. For our task we use the opening and closing price to calculate if the stock went up or down on one day.

B. Google Trends data

google trends data

1) Hacking Google Trends:

- google trends has no api unlike many other google services
- therefore, an analysis of the request url was done to send prepared requests for data collection
- some additional problems like max. number of requests, request blockade etc.

C. Merged dataset

From the three previously described datasets we used only two directly. The NYSE dataset (see VI-A1) was only used to collect data from *Google Trends* (see VI-B). We combine the data of 14 search terms with the data from S&P500 (see VI-A2). We integrated the label in our dataset. The label is calculated from the opening and closing price.

$$y = \text{sign}(p_{\text{close}} - p_{\text{open}}) \quad (1)$$

The label can be found in the first column so that we can easily extract it in our algorithm. We separate our data in two classes. A label of 1 means that the stock went up on this day. The other class is labeled with -1 and says that the price went down. If the value did not change during the day the label will be 0. We interpret it the same as the label -1 because only up going prices are good if you invested in this stock.

The second column contains the opening price we already used to calculate the label. We did not include the closing value because it is the same as the opening price of the following day and could be computed. We include one price so that our network can use it to compare the trend of the stock price with the trends of the search terms. The value may be used to not only predict if the stock goes up or down, but to predict the exact next value.

The columns 3 to 16 contain the values of the search terms. It is important that there are only a few values of zeros. One problem is to find good search terms which are really

correlated to the trend of the stock price. It is easily possible to replace them and test the network with other search terms. This may improve the prediction. We always include the search terms for the ticker symbol and the company name. The remaining twelve search terms depend on them.

Unfortunately it was not possible to collect data from *Google Trends* for all search terms for the last five years. Therefore, we had to discard some of the stock prices and start including them in our dataset as soon as there are enough search terms with a different value than 0. That is why the trends are starting at a different date. The dataset can be preprocessed. Our preprocessing is described in the following chapter.

VII. PREPROCESSING

zero centering

- csv format
- zero centering
- ...

VIII. MODEL DEFINITION

used model (kind of lstm), tensorboard

- logical representation of the model
- lstm/rnn: why?

IX. IMPLEMENTATION DETAILS

X. EVALUATION

- describe how the implementation is being evaluated
- execute the evaluation
- describe and interpret the results

XI. CONCLUSION

- summarize the results (implementation? evaluation results?)
- does it work? why? why not?
- how could the current solution be improved?
- possible further research?

LITERATUR

- C. Chong, Eunsuk and Han and F. C. Park. Deep learning networks for stock market analysis and prediction. *Expert Syst. Appl.*, 83(C):187–205, Oct. 2017. ISSN 0957-4174. doi: 10.1016/j.eswa.2017.04.030. URL <https://doi.org/10.1016/j.eswa.2017.04.030>.
- D. Gawlik. New york stock exchange, 2017. URL <https://www.kaggle.com/dgawlik/nyse>.
- C. Nugent. S&p 500 stock data, 2017. URL <https://www.kaggle.com/camnugent/sandp500>.
- R. Singh and S. Srivastava. Stock prediction using deep learning. *Multimedia Tools Appl.*, 76(18):18569–18584, Sept. 2017. ISSN 1380-7501. doi: 10.1007/s11042-016-4159-7. URL <https://doi.org/10.1007/s11042-016-4159-7>.