**Comparative analysis of machine learning models incorporating technical analysis *(+sentiment)* to set up algorithimic trading strategy**

**Comparative performance analysis between traditional machine model and deep neural network on setting up technical stock trading strategy**

**Equity market index (DAX) direction prediction with LR, SVM, RF(NLP) and LSTM nueral networks**

Broad objective: To identify simple but profitable trading strategy for individual investors based on different or hybrid models developed through machine learning algorithms

Specific objective:

1. Predict DAX index
2. Evaluate the different model performance on the predictions
3. Compare profitability of the individual models

Trading Limitations:

1. Active investment (long and short) through single index fund
2. No transaction and management fees are taken into account

Thesis report framework:

Lit review, general objectives, data preparation, data exploration, model, findings, further scope

**Literature review summary:**

Many market participants now employ AT, commonly defined as the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission. From a starting point near zero in the mid‐1990s, AT is thought to be responsible for as much as 73 percent of trading volume in the United States in 2009 [“SEC runs eye over high‐speed trading,” Financial Times, July 29, 2009]. The stock prices of the same industry have a similar trend, but those of different industries do not. When investing in stocks of different industries, one should select the optimal model from lots of trading models for each industry because any model may not be suitable for capturing the stock trends of all industries. However, the study has not been carried out at present. In this paper, firstly we select 424 S&P 500 index component stocks (SPICS) and 185 CSI 300 index component stocks (CSICS) as the research objects from 2010 to 2017, divide them into 9 industries such as finance and energy respectively. Secondly, we apply 12 widely used machine learning algorithms to generate stock trading signals in different industries and execute the back-testing based on the trading signals. Thirdly, we use a non-parametric statistical test to evaluate whether there are significant differences among the trading performance evaluation indicators (PEI) of different models in the same industry. Finally, we propose a series of rules to select the optimal models for stock investment of every industry. The analytical results on SPICS and CSICS show that we can find the optimal trading models for each industry based on the statistical tests and the rules. Most importantly, the PEI of the best algorithms can be significantly better than that of the benchmark index and “Buy and Hold” strategy. Therefore, the algorithms can be used for making profits from industry stock trading [Lv D, Huang Z, Li M, Xiang Y (2019) Selection of the optimal trading model for stock investment in different industries]. Traditional machine learning models map the feature space to the target space. The parameters of the learning model are less. Therefore, the learning goal can be better accomplished in the case of fewer data. Moreover, traditional machine learning algorithms usually use interpretable mathematical methods such as support vector machines to build a learning task or model learning tasks based on clear and explicit rules such as decision trees. Huang et al. used SVM to forecast the weekly movement direction of the NIKKEI 225 index and compared its performance with Linear Discriminant Analysis [Huang W, Nakamori Y, Wang SY. Forecasting stock market movement direction with support vector machine. Computers & Operations Research. 2005; 32: 2513–2522.]. Chen applied SVM to do pattern recognition in the financial engineering domain [Chen JX. SVM application of financial time series forecasting using empirical technical indicators. In International conference on information, networking and automation; 2010]. Xie used SVM to forecast the closing price on the third day and optimized the parameters of the model with particle swarm algorithm [Xie CQ. The optimization of share price prediction model based on support vector machine. In International conference on control, automation and systems engineering; 2011]. Ladyzynski et al. presented a novel architecture of the system for automated stock trading, which applied RF, trend detection tests and force index volume indicators to investigate if machine learning was able to predict future trends. The results showed that the system failed to generate a profitable trading strategy [Ładyżyński P, Żbikowski K, Grzegorzewski P. Stock Trading with Random Forests, Trend Detection Tests and Force Index Volume Indicators. International Conference on Artificial Intelligence and Soft Computing; 2013]. Zhang et al. used an unsupervised heuristic algorithm to cut transaction data into four main classes, and the class prediction models were trained by a combination of RF, imbalance learning and feature selection [Zhang J, Cui SC, Xu Y, Li QM, Li T. A novel data-driven stock price trend prediction system. Expert Systems with Applications. 2018; 97:60–69]. Ruta used LR as the class method and learned to generate profit from multiple inter-market price predictions and markets’ correlation [Ruta D. Automated Trading with Machine Learning on big data. IEEE International Congress on Big Data; 2014.]. Patel compared four stocks predicted models, ANN, SVM, RF, and NB on 10 years of two group historical data, and the results showed that using trends deterministic data could improve predicted performance [Patel J. Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques. Expert Systems with Applications. 2015; 42:259–268]. Luo et al. integrated piecewise linear representation (PLR) and weighted SVM to forecast the stock trading signals, and the comparative experiments on 20 shares from Shanghai Stock Exchange in China showed that the predicted accuracy and profitability was effective [Luo LK, Chen X. Integrating piecewise linear representation and weighted support vector machine for stock trading signal prediction. Applied Soft Computing. 2013; 13(2):806–816]. Zbikowski used volume weighted SVM with walkforward testing and feature selection for the purpose of creating a stock trading strategy, and the trading strategy results of given methods could improve trading performance [Zbikowski K. Using Volume Weighted Support Vector Machines with walk forward testing and feature selection for the purpose of creating stock trading strategy. Expert Systems with Application. 2015; 42:1797–1805]. Dash et al. proposed a novel decision support system using a computational efficient functional links artificial neural network and a set of rules to generate the trading decision [Dash R, Dash PK. A hybrid stock trading framework integrating technical analysis with machine learning techniques. The Journal of Finance and Data Science. 2016; 2:42–57]. In recent years, the applications of deep neural network algorithms in finance have attracted more and more attention. These algorithms mainly connect some neurons into multiple layers to form a complex deep neural network structure. Through this complex structure, the mapping relationship between input and output is established. As the number of layers of the neural network increases, the neural network can automatically adjust the weight parameters to extract advanced features. The deep neural network models have many parameters compared with the traditional machine learning models, so the performances of deep neural network models tend to increase as the amount of data grows. Of course, deep learning has high requirements for computing hardware; deep neural networks use nested hierarchy structure to perform representation learning, so deep learning algorithms are less interpretable. Bao et al. presented a deep learning framework, which combined wavelet transform(WT), SAE and LSTM for stock price forecasting [Bao W, Yue J, Rao YL. A deep learning framework for financial time series using stacked autoencoders and long short term memory. Plos ONE. 2017; 12(7):1–24]. Thomas et al. deployed LSTM to predicted out-of-sample directional movements for the constituent stocks of the S&P 500 index [Thomas F, Chrisstopher K. Deep learning with long short-term memory networks for financial market predictions. Fau Discussion Papers in Economics. 2017; 270(2):1–32]. Makickiene et al. proposed a new method of orthogonal input data to improve the process of RNN learning and financial forecasting [Makickiene N, Rutkauskas AV, Maknickas A. Investigation of financial market prediction by recurrent neural network. Innovative Info Technologies for Science, Business and Education. 2011; 2(11):1–24]. Persio et al. compared different RNNs architectures such as multi-layer RNN, LSTM and GRU performances on forecasting Google stock price movements [Persio LD. Recurrent neural networks approach to the financial forecast of Google assets. International Journal of Mathematics and Computers in Simulation. 2017; 11:1–7]. Dunis et al. applied three different types of neural network including MLP and RNN to trade oil futures spreads in the context of a portfolio of contracts [Dunis CL, Laws J, Evanset B. Trading futures spread portfolios: applications of higher order and recurrent networks. The European Journal of Finance. 2008; 14(6):503–521]. Chong et al. proposed a systematic analysis of the use of deep learning networks for stock market analysis and prediction, and examine the effect of three unsupervised feature extraction methods on the ability of deep neural networks to forecast future market behavior [Chong E, Han C, Park FC. Deep learning networks for stock Market analysis and prediction: Methodology, data representations, and case studies. Expert Systems with Applications. 2017; 83:187–205]. Krauss et al. implemented and analyzed the effectiveness of deep neural networks, gradient-boosted-trees, RF, and several ensembles of these methods in the context of statistical arbitrage, and the experimental findings were promising [Krauss C, Do A, Hucket N. Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P500. European Journal of Operational Research. 2017; 259: 689–702]. Hsieh et al. used WT and RNN to forecast stock markets, which based on an artificial bee colony algorithm [Hsieh TJ, Hsiao H, Yeh W. Forecasting stock markets using wavelet transforms and recurrent neural networks: An Integrated system based on artificial bee colony algorithm. Applied Soft Computing. 2011; 11(2):2510–2525]. La¨ngkvist et al. gave a review of some development in deep learning and unsupervised learning for time series problems and pointed out some challenges in this area [La¨ngkvist M, Karlsson L, Loutfiet A. A review of unsupervised feature learning and deep learning for time-series modeling. Pattern Recognition Letters. 2014; 42:11–24]. Liu et al. gave some widely-used deep learning architectures and their applications, and the models included autoencoder, DBN, and restricted Boltzmann machine(RBM) [Liu WB, Wang ZD, Liu XH, Zeng NY, Liu YR, Alsaadi DE. A survey of deep neural network architectures and their applications. Neurocomputing. 2017; 234:11–26]. Dixon applied RNNs to high- frequency trading and solved a short sequence classification problem of limit order book depths and market orders to predict the next event price-flip [Dixon M. Sequence classification of the limit order book using recurrent neural networks. Journal of Computational Science. 2018; 24:277–286]. Kim et al. proposed a hybrid LSTM model to predict stock price volatility that combined the LSTM with various GARCH-type models [Kim HY, Won CH. Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. Expert Systems with Application. 2018; 103: 25–37]. Shen et al. applied GRU and its improved version for forecasting trading signals for three stock indexes and compared proposed models with the traditional deep network and the other popular models [Shen GZ, Tan QP, Zhang HY, Zeng P, Xu JJ. Deep Learning with Gated Recurrent Unit Networks for Financial Sequence Predictions. Procedia Computer Science. 2018; 131:895–903]. Sezer et al. proposed a deep neural network based stock trading systems evolutionary optimization technical analysis parameters to improve the stock trading performance [Sezer OB, Ozbayoglu M, Dogdu E. A Deep Neural-Network Based Stock Trading System Based on Evolutionary Optimized Technical Analysis Parameters. Procedia Computer Science. 2017; 114:473– 480].

*Research gap:*

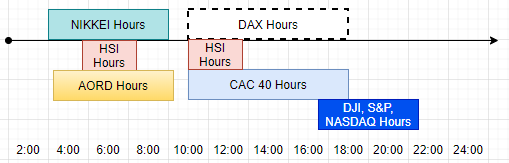
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**Schema**

For **regression analysis**, 9 indices across Asia, Europe and USA are analyzed. The price information is from 01.01.2009 to 30.04.2020 (approximately 2869 days).

Daxi~daxi\_lag1+cac40+hsi+nikkei+sp500+spy+nasdaq+dji+Price+aord

His and Aord significant, correlation. But inferential statistics cannot be used since there is scope of multicollineraity. There is heteroscedasticity as well. Sharpe around 3. Maximum drawdown is around 10%.

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For **NLP**, data were collected from kaggle. Data from (2000-01-03 to 2016-07-01). Should it be consistent with the regression model? Used random forest model. Accuracy is 53%. (may use NLTK in the future).

LSTM. The price information is from 01.01.2009 to 30.04.2020 (approximately 2869 days). The close price data of 60 days is used to predict the 61st day value. High RMSE.

**Kanban board for thesis**

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| **Backlog** | **To Do** | **In progress** | **Done** |
| Collect data for NLP (stock twits, or prepared data) | Finalize thesis topic and formalities | Formal report writing on Literature review  Deadline: May 25 | 1st draft model development:  Regression, NLP, LSTM |
| Try NLTK library for the NLP | Get step-by-step model feedback | Develop SVR model (subject to approval) |  |
| Develop ML model that uses other stock indices to predict DAX | Formal report writing on data preparations, data exploration, model explanation segments  ~June 6 | Improve accuracy of the models (try different libraries (pytorch/tensorflow)  Deadline: May 30  *Normalize data for NLP* |  |
| Study hybrid models (combination of models to predict DAX) | Writings on findings and scope of further studies  ~June 10 |  |  |
| Try to develop hybrid model development | First draft of the report and feedback  ~June 12 |  |  |
|  | Feedback from professor |  |  |
|  |  |  |  |

Lstm weakness: <https://www.blueskycapitalmanagement.com/machine-learning-in-finance-why-you-should-not-use-lstms-to-predict-the-stock-market/>

**Trading vs investing: Introduction**

Buy side vs sell side.

The organizations that are involved in advising and investing as their primary business activities belongs to the buy side. These are hedge funds, asset managers and others in the form of private equity, insurance, pension and mutual funds. The sell side companies (banks and brokers) acts as intermediaries to support the buy side companies. In investment firms there are portfolio managers making a variety of strategic and tactical decisions. Strategic decisions involve asset category selection for the long-term to ensure diversity. Tactical decisions are short-term actions that select specific assets to long or short within each asset category. To buy and hold undervalued equity classes through fundamental analysis is the most frequently used investment strategy. The success or failure of the portfolio managers depends on the extent of outperformance relative to the benchmark index. In case of hedge funds, a team of quants, developers and academics work in collaboration to generate positive return irrespective of the market performance. This return of hedge funds, known as Alpha, though used by the portfolio managers to express their performance, there is

Source:

Strategic allocation decides how much to invest in each asset category such as equities, bonds, real estate, or commodities. Tactical allocation chooses specific assets to buy or short within each category. The most common investment strategy is to buy and hold assets that had been identified as undervalued based on fundamental analysis. Portfolio managers' gains and losses are measured relative to a relevant benchmark, portfolio, or index which mirrors their strategic allocation in their portfolio. This performance is measured net of any moves in the benchmark or index. So they can only outperform if their asset choices beat a passive portfolio that mirrors the benchmark. Hedge funds on the other hand, we find traders, developers, and researchers all working together to identify and implement quantitative strategies. Their goal is to generate a positive return that is independent of overall moves in the market. This hedge return is called Alpha. The term Alpha is also widely used by portfolio managers to refer to their outperformance or return above a benchmark. This excess return seems similar to the Alpha generated by hedge funds, but there's an important difference. Portfolio manager Alpha comes from long asset holdings that are exposed to market, sector, and company risk as opposed to hedge fund Alpha which comes from a hedge strategy that has eliminated or at least attempted to minimize these risks. This is one of the key benefits of investing in a hedge strategy, especially if you're worried there'll be a sell off in the overall market. Portfolio managers use fundamental analysis to rebalance the allocations in their portfolios. Rebalancing includes changes in the strategic allocation to give undervalued asset categories a heavier weight in the portfolio. It can also include tactical reallocation, where ideally you're selling winning assets that have achieved their full target value and replacing them with undervalued assets that have the potential to help the portfolio achieve returns in excess of its benchmark. At trading firms, traders have a much shorter-term opportunistic focus. The time frame for their investments ranges from a few months to a few milliseconds. A millisecond end of this spectrum dominates over all trading volume. Traders rarely use fundamental analysis as a factor in their decisions as they consider this information to already be baked in to the market price and essentially worthless for generating Alpha. Traders instead look constantly for market behaviors and inefficiencies that will generate high-risk adjusted returns on their trading capital. Although they trade the same assets as portfolio managers, they generally ignore fundamentals and focus on other sources of mispricing. Buy-side quantitative methods include regression, prediction models, statistical arbitrage, and machine learning which we'll cover later in the course. Sell-side quantitative methods are mostly execution strategies. These are designed to reduce the market impact cost of large orders and also to capture spreads by providing liquidity through market making. Keep in mind though that buy-side firms also employ execution strategies when they execute their trading orders.