Algorithmic Trading using Accounting Ratios

Research report

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The current report intends to analyse how the ideas outlined in Olson, Mossman (2003)[1] *can be applied to the modern dataset of Chinese stocks available at Kaggle*[2]*. All the results can be directly replicated using the public repo*[3] *following the instructions of the "README.md" file.*

1 Paper Analysis

The main idea of the original paper was encapsulated in the construction of the 4 strategies with yearly frequency using the machine learning algorithms. For each of the strategies, a dataset of numerous accounting ratios was collected over a span of 18 years, which subsequently was used for training and inference of models. The time-frame of the dataset collected was from 1976 to 1993, and contained data of exclusively Canadian stocks. After the authors conclude their explanation of the data, they outline the methodology of prediction for each of the strategies, which presumed that the first 6 years of data were used for training of machine learning models and then rolled forward for inference for each subsequent years, i.e. for each inference step the models were first trained and then the prediction were made. Additionally, each of the strategies, which essence will be explained shortly, was categorized into 2 groups: one being based on the regression methods, and another based on the classification techniques.

The first strategy explained in the paper used standard OLS regression to predict one-year-ahead return of an arbitrary stock. The dataset over the previous 6 years of data was collected in the pooled-data form, i.e. the time-period of a particular observation was disregarded and each entry was used with equal weight for training the data. Then, the authors suggested 3 various trading rules how the portfolio can be constructed: the first rule was based on the median cut-off decision rule which consisted in buying all the stocks which predicted returns were over the median value of the overall prediction dataset, and similarly the stocks below the median value were sold. The weights of each purchased or sold stock were distributed uniformly. Another possible trading rule was governed by the quartile cut-off values, where the portfolio was formulated of buying all the stocks which are in the upper quartile and selling all the stocks that are in the lower quartile, leaving all other assets unattended. Finally, the last rule was governed using the same techniques but with octile intervals.

The second strategy, which on the contrary was based on the classification techniques, employed the means of the Logistic regression. Such strategy was using the same data as the regression model, but rather than yielding returns for each of the observations, it was predicting the probabilities for each of the stocks being in the certain category. The trading rule of such strategy, as well as construction of such categories, was done as follows: rather than selecting stocks based on the median, quartile, or octile ranks of forecasted returns, the data was preprocessed initially into 2, 4, or 8 categories based on the percentiles of the observed returns, i.e. for the median trading rule the observed returns of stocks were put into the bins depending

[1] Olson, Dennis & Mossman, Charles. (2003). Mossman, Neural Network Forecasts of Canadian Stock Returns using Accounting Ratios. International Journal of Forecasting. 19, 453-465. International Journal of Forecasting. 19. 453-465.

[2] https://www.kaggle.com/datasets/franciscofeng/augmented-china-stock-data-with-fundamentals

[3] https://github.com/vladargunov/strategy-ratios

whether their returns exceeded the median return over the whole sample. Then, in a similar fashion with the previous strategy, the logistic model predicted the categories of the future returns of the stocks and the portfolios were formed based on the respective category for each of the predicted results. For example, for the median rule all the stocks predicted to be placed in the category of above median returns were purchased with uniform weights, and all the other stocks were sold. Respectively, for the quartile decision rule all the stocks predicted to be in the upper quartile were bought, while all the stocks predicted to be in the lower quartile were sold.

The two final strategies followed absolutely the same trading and dataset construction rules, but their underlying models were rather based on the deep neural networks with one hidden layer and hyperbolic tangent activation function. That is, if the network to be employed was of the regression type, the final loss was chosen to be of the MSE type, and the trading rules were identical to the rules of ordinary linear regression. However, if the model was chosen to be of the classification type, the same preprocessing of data as in the case of logistic regression was done and the final loss of the network was chosen to be the CrossEntropy loss. The authors of the paper were not explicit about the details how they constructed their networks, but my main conjecture that they used the above mentioned structures to obtain their results.

2 Current implementation

Finally, it is time to move on to our implementation of the mentioned strategies. We will try to replicate the ideas and the analysis of the paper as close as possible, however, due to dataset constraints and improvement in the software some amendments will have to be made. For instance, instead of yearly frequency the strategies are implemented at monthly execution. Additionally, in order to account for weekends and Chinese holidays, if the trading day falls for one of each dates, then the trading decision will be made on the next closest day where stock prices are available, and then the next time interval starts from such date. For example, if the trading strategy started on 01-01-2021 and moved to the next date 01-02-2021, which turned out to be the weekend, the trade will be executed on 02-02-2021, and the next trade will fall on the 02-03-2021, so the interval between trades remains to be at least monthly.

With regard to the dates of the algorithm, we let each of the strategies to be trained on the 6 last months before the testing period which starts on 01-01-2021 and ends by 11-05-2022, but we do not trade our strategies afterwards, so all the predictions are made based on the single training dataset. Finally, all the data is scaled to have zero mean and unity variance before entering the training and inference phases of all the algorithms.

3 Empirical results

For each of the 4 outlined strategies, we perform 3 simulations for each of the trading rules, getting the following results for sharpe and return-to-drawdown metrics. In these examples, the former metric is computed as the average of returns for each date with subtracted risk-free interest rate, which was chosen to be 0.01, divided by the standard deviation of such returns, while the latter metric is computed as the last value of the portfolio divided by the lowest value.

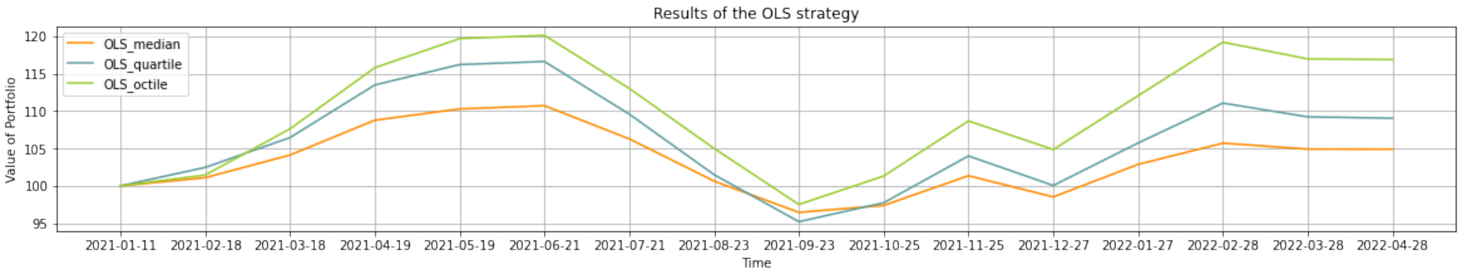
Table 1: Sharpe ratios (1)

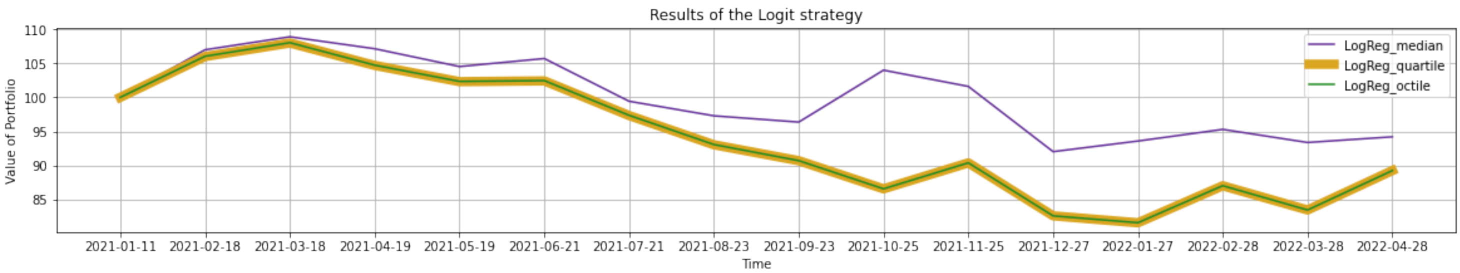
Strategy / Trading rule	Median	Quartile	Octile
OLS	0.61	0.89	1.34
Logit	-0.17	-0.84	-0.83
NN Regression	-0.1	-0.43	-1.36
NN Classification	-0.63	1.63	-1.24

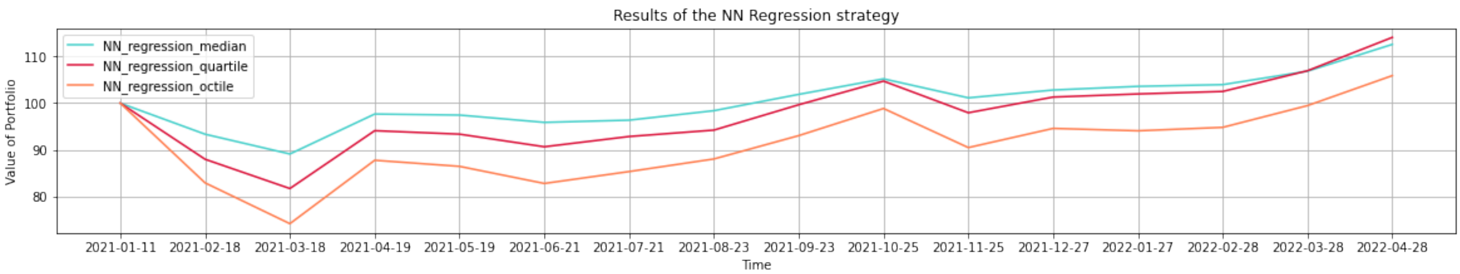
Table 2: Return to drawdown metrics (1)

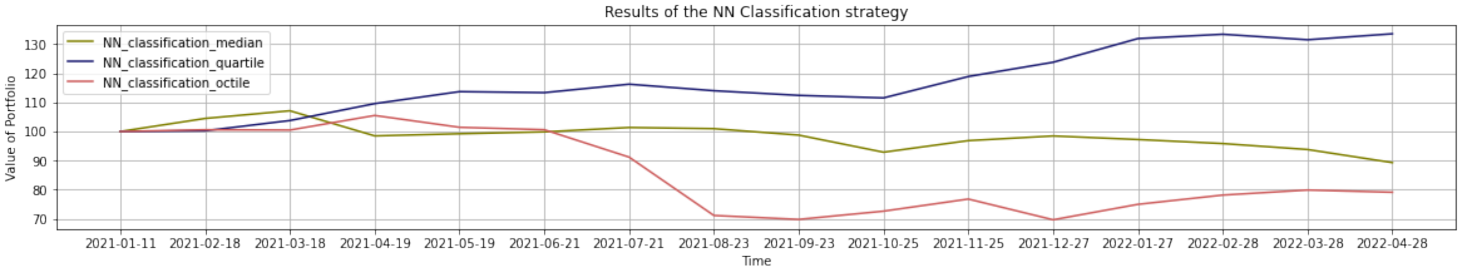
Strategy / Trading rule	Median	Quartile	Octile
OLS	1.09	1.15	1.2
Logit	1.02	1.09	1.09
NN Regression	1.26	1.4	1.43
NN Classification	1.00	1.34	1.14

Following the results, it is clear that Logit and Neural Regression strategies showed the worst returns over the course of testing period, while the best strategy turned out to be the Neural Classification with Quartile decision rule, leading to the 1.63 sharpe ratio. Additionally, all standard OLS strategies also showed positive sharpe returns, with maximum being the 1.34. As for the graphical representation of the changes in value for each of the strategies, the graphs below are produced.









Additionally, we report the values for the shortened period of time which assumes to be started on 2022-01-01. The computation of the same metrics leads to the following summaries

Table 3: Sharpe ratios (2)

Strategy / Trading rule	Median	Quartile	Octile
OLS	3.38	3.27	4.18
Logit	-0.29	1.75	1.75
NN Regression	0.88	1.02	1.11
NN Classification	-1.91	-0.45	4.7

Table 4: Return to drawdown metrics (2)

Strategy / Trading rule	Median	Quartile	Octile
OLS	1.02	1.03	1.04
Logit	1.01	1.09	1.09
NN Regression	1.09	1.12	1.13
NN Classification	1.00	1.02	1.06

While the metrics produced appeared to be more extreme, which is more likely due to the shorter sample, the general pattern remained the same, that is the OLS and Neural Classification strategies yielded better returns rather than Logit and Neural Regression models. However, my recommendation is not to trust these metrics since for each of strategies we have obtained only 4 trades, leading to the greater variance and not objective results. For more trustworthy results please refer to the original tables.

4 Conclusion

While some strategies showed decent results on the testing interval, the scope for improvement of the above strategies largely remains unexplored. With this regard the reader is invited to test his own strategies by altering the trading interval, changing the hyperparameters, frequency, or decision rules, as well as suggesting her own trading ideas. Most of the necessary tools I tried to provide in the code published and in the future I will try to write a more extensive manual how it is possible to work with the code.