Automatic construction of neural networks for stock market trend prediction

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Abstract. Although significant work has been done for hyperparameter optimisation (HO) for deep learning structures in general, there is limited research exploring their use for time series applications, such as stock market prediction. In this research we evaluate the potential for automating structure learning and hyperparameter selection for neural networks for stock market trend prediction with a limited computational budget. We evaluate Bayesian Optimisation and Hyperband (BOHB), for automatic construction of LSTM and CNN models, and compare these to manually tuned models. The results show that the BOHB technique can select CNN and LSTM models that can compete against manually tuned models.

Keywords: Stock Market · Trend Prediction · Automated Hyperparameter Optimisation · Neural Networks.

1 Stock trend prediction problem, and hyperparameter optimisation

Given a stock market index such as S&P 500, we aim to classify the next day trend direction (UP or DOWN) using the last l days price sequence. Wen et al. [6] recently tackled it using a convolutional neural networks (CNN) based approach whereas Guo and Li [3] proposed a long-short term memory (LSTM) recurrent neural networks approach.

The hyperparameter optimisation problem is about finding the optimal hyperparameter configuration that minimises the loss function of a learning algorithm over its hyperparameter space when trained on a training dataset and evaluated on the corresponding evaluation set.

2 Experimental Design

To evaluate the effectiveness of BOHB [2], we compared the performance of the hyperparameters found with BOHB against manually tuned baselines. The baselines consists of a manually tuned CNN and a manually tuned LSTM using S&P 500 dataset, and Wen et al. [6], and Guo and Li's [3] results, where applicable.

We used the the daily stock closing price of the S&P 500, JSE Limited (JSE), NASDAQ and Dow Jones 30 (DOW 30), with lag $l = 10$, and stride $s = 1$. We used 70% of the dataset for training, 15%, for validation and 15% for testing. Similar to Wen et al. [6], and Guo and Li [3], we used accuracy, and f1-score (f1) as generalisation metrics. We used HyperbandSter[3] [2] with the number of epochs as budget where the minimum budget was 3 epochs and the maximum budget 30 epochs. We set η to 3 and used 30 iterations. This is equivalent 80 full evaluations. Each experiment was run 10 times.

3 Results and Discussions

The performance on the 8 individual datasets are shown in table 1.

Table 1. Comparison of BOHB (A) with the manually tuned baselines (M)

Method	S&P 500		NASDAQ		DOW 30		JSE		SH		SZ		CSI 300		SSE 50	
	acc.	f1	acc.	f1	acc.	f1	acc.	f1	acc.	f1	acc.	f1	acc.	f1	acc.	f1
A-CNN	53.26	67.66	54.30	63.46	53.33	**68.80**	**89.33**	**94.35**	47.88	**50.46**	52.40	**42.34**	49.33	**41.45**	**51.15**	36.45
M-CNN	**53.73**	**67.95**	**54.74**	**69.26**	**53.68**	68.00	83.86	90.93	**48.72**	43.94	**55.45**	21.33	**57.05**	31.01	47.44	**47.27**
A-LSTM	53.53	68.26	**55.56**	71.04	52.90	67.53	88.89	94.11	**48.27**	52.53	**47.98**	49.83	**49.62**	52.91	**50.67**	53.46
M-LSTM	**53.73**	***69.74***	**55.56**	**71.25**	**53.83**	**69.83**	**90.44**	**94.95**	45.19	***61.74***	39.74	***56.88***	41.67	***58.45***	49.04	***65.66***
Wen	*56.14*	63.67	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Guo	-	-	-	-	-	-	-	-	*55.89*	42.99	*64.13*	37.49	*67.25*	46.51	*59.52*	43.99

On the individual datasets, A-CNN improved on 7 metrics over M-CNN, under-performed on 9; whereas, A-LSTM out-performed M-LSTM on 4 metrics, and under-performed on 11. For NASDAQ, A-LSTM matched the accuracy of the manual LSTM. Compared to the results found in the literature by Wen. et al [6] and Guo and Li [3], our methods under-performed on accuracy but out-performed on f1-score. On average, A-CNN improved on M-CNN's and f1-score by 5.75% (54.96 ± 23.06 to 58.12 ± 19.28); but, decreased on accuracy by 0.81% (56.83 ± 11.40 to 56.37 ± 13.49). A-LSTM on the other hand, could not match M-LSTM on f1-score with a performance drop of 7.07% (68.56 ± 11.95 versus 63.71 ± 14.89). However, it beat M-LSTM on accuracy by 4.74% (53.40 ± 16.24 versus 55.93 ± 13.58).

4 Conclusions

We evaluated the potential for automatic construction of CNN and LSTM for stock market trend prediction in a resource constrained setting. Our results showed that BOHB can compete favourably with manual HO.

[1] https://finance.yahoo.com/
[2] https://www.investing.com/
[3] https://github.com/automl/HpBandSter

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