

Stock Price Forecasting Based On TRUST-TECH Enhanced ANNs

Chengjie Lin, Mo He (mh2394), Jiamin Zeng (jz863), ECE MEng, Cornell University
Prof. Hsiao-Dong Chiang V2

Introduction

Mathematical models like Deep learning, as a purely data-driven approach, proved to be powerful in big data analysis and is of great significance to future markets.

Traditionally, Long-short Term Memory is to be used to make predictions in time series financial fields like stock price. The innovation introduced is applying the Transformation Under Stability-retaining Equilibrium Characterization (TRUST-TECH) into the deep learning neural networks training process, whose main features include its capability in identifying multiple local optimal solutions in a deterministic, systematic, and tier-by-tier manner.

Background

Stock Price Forecasting

Long-Short Term Memory (LSTM)

- Suitable for stock market prediction for the trading, e.g. buying and selling of financial instruments
- A challenging short-term time-series prediction due to its noise and volatile features
- Training may easily fall into a local optimum

TRUST-TECH Methodology

(Transformation Under Stability-reTaining Equilibria Characterization)

- Motivation: Use local optimum to find global optimum
- One-to-one correspondence: local optimal solution & Stable Equilibrium Point (SEP) in dynamical system
- Jump to Tier-1 EP iff the solution is better

Implementation

Preparation and Setup

6-year-data (12'-18'), Time-series, Daily stock price in USD, Care about 'close'

Dataset

Environment Setup

Environment Setup

Naive LSTM Model for Stock Price Prediction

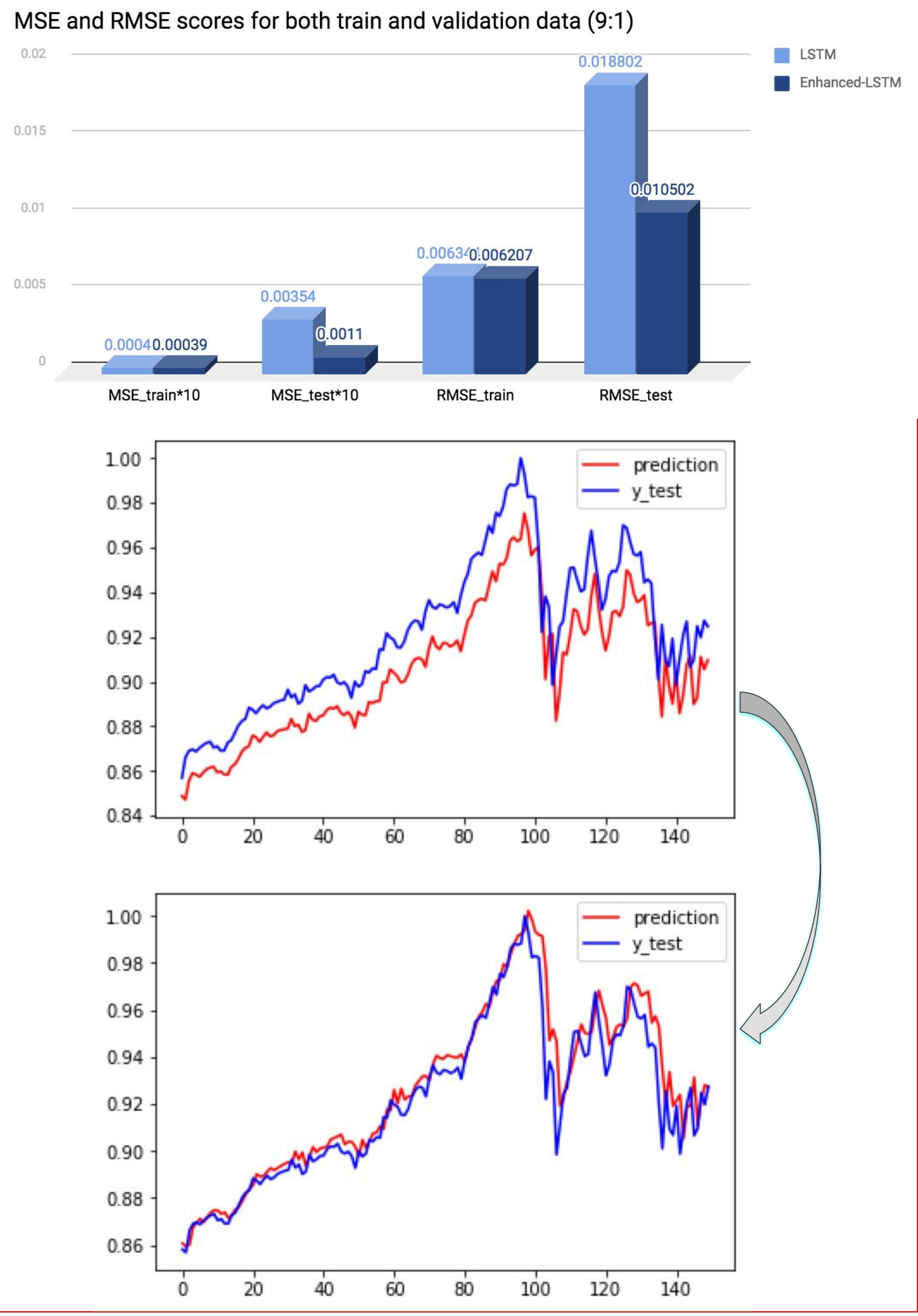
Windowing is utilized in this project. To predict future stock price, raw data is first converted to time series data in each of whose entries features contains open, high, low and close price of 5-day period, label is loaded with the close price on the 6th day. 2 layers of LSTM with 0.2 dropout and 2 dense layers with activation functions are constructed when 0.1 validation is set to validate the score.

Predictive Mechanism

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 5, 32)	4736
dropout_1 (Dropout)	(None, 5, 32)	0
lstm_2 (LSTM)	(None, 16)	3136
dropout_2 (Dropout)	(None, 16)	0
dense_1 (Dense)	(None, 1)	17
dense_2 (Dense)	(None, 1)	2
Total params: 7,891		

Model Layers

Result



Discussion

- ❑ Dimensionality of each time slot data
- ❑ Unpredictable economical changes
- ❑ If training may easily fall into a local optimum, potential power of Neural Net has not been fully explored

References

1. Wang, B. D., Hsiao-Dong Chiang. 2011."ELITE: Ensemble of Optimal, Input-Pruned Neural Networks Using TRUST-TECH."IEEE Transactions on Neural Networks22(1): 96-109.
2. Tang L, Chiang H-D. Toward high-performance stock price forecasting using an ensemble of trust-tech-enhanced neural networks. 2015.
3. H. D. Chiang, C. C. Chu, "A systematic search method for obtaining multiple local optimal solutions of nonlinear programming problems", IEEE Transactions on Circuits and Systems: I Fundamental Theory and Applications, vol. 43, no. 2, pp. 99-109, 1996.
4. Chiang, Hsiao-Dong & Reddy, Chandan. (2007). TRUST-TECH based neural network training. IEEE International Conference on Neural Networks - Conference Proceedings. 90 - 95. 10.1109/IJCNN.2007.4370936.

Acknowledgements

Special thanks to Prof. Hsiao-Dong Chiang, advisor of this Master of Engineering Design Project, for giving us advise and feedbacks in completing this project. His support has been outstanding throughout the project implementation.