



# Using LSTM in Stock prediction and Quantitative Trading

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Video: [https://www.youtube.com/watch?v=K3w\\_zsz1qYI](https://www.youtube.com/watch?v=K3w_zsz1qYI)

## I. Motivation

- Accurate prediction on finance market will yield attractive profit
- Traditional methods rely on subjective views on economy and company's future direction
- Quantitative methods start to leverage machine learning to avoid human subjectivity and emotion



Figure 1. Deep learning is expected to help avoid stock plunge and generate profit.

## II. Data & Features

Historical daily stock price and quarterly reported corporate accounting statistics were collected from Kaggle Open Dataset and merged by date.

- Train set: 2004 to 2011
- Dev set: 2012
- Test set: 2013
- Features: adjusted close price, trade volume, 'Debt-to-Equity Ratio', 'Return on Equity', 'Price-to-Book' ratio, etc.

| date       | adj_close | volume   | DE Ratio | Return on Equity | Price/Book | Profit Margin | Diluted EPS | Beta    |
|------------|-----------|----------|----------|------------------|------------|---------------|-------------|---------|
| 2013-12-17 | 0.950181  | 0.019849 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-18 | 0.964789  | 0.036554 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-19 | 0.966209  | 0.023068 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-20 | 0.980317  | 0.062588 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-23 | 0.994504  | 0.024452 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-24 | 0.991310  | 0.000000 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-26 | 0.996816  | 0.014948 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-27 | 0.997737  | 0.020691 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-30 | 0.988978  | 0.012428 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |
| 2013-12-31 | 1.000000  | 0.015446 | 0.652485 | 0.01414          | 0.046009   | 0.626554      | 1.0         | 0.24031 |

Figure 2. An example of input data structure

## III. Models

Both classic time series and deep learning models were experimented:

- Linear model (ARIMA)
- Single-LSTM
- Stacked-LSTM
- Attention-LSTM

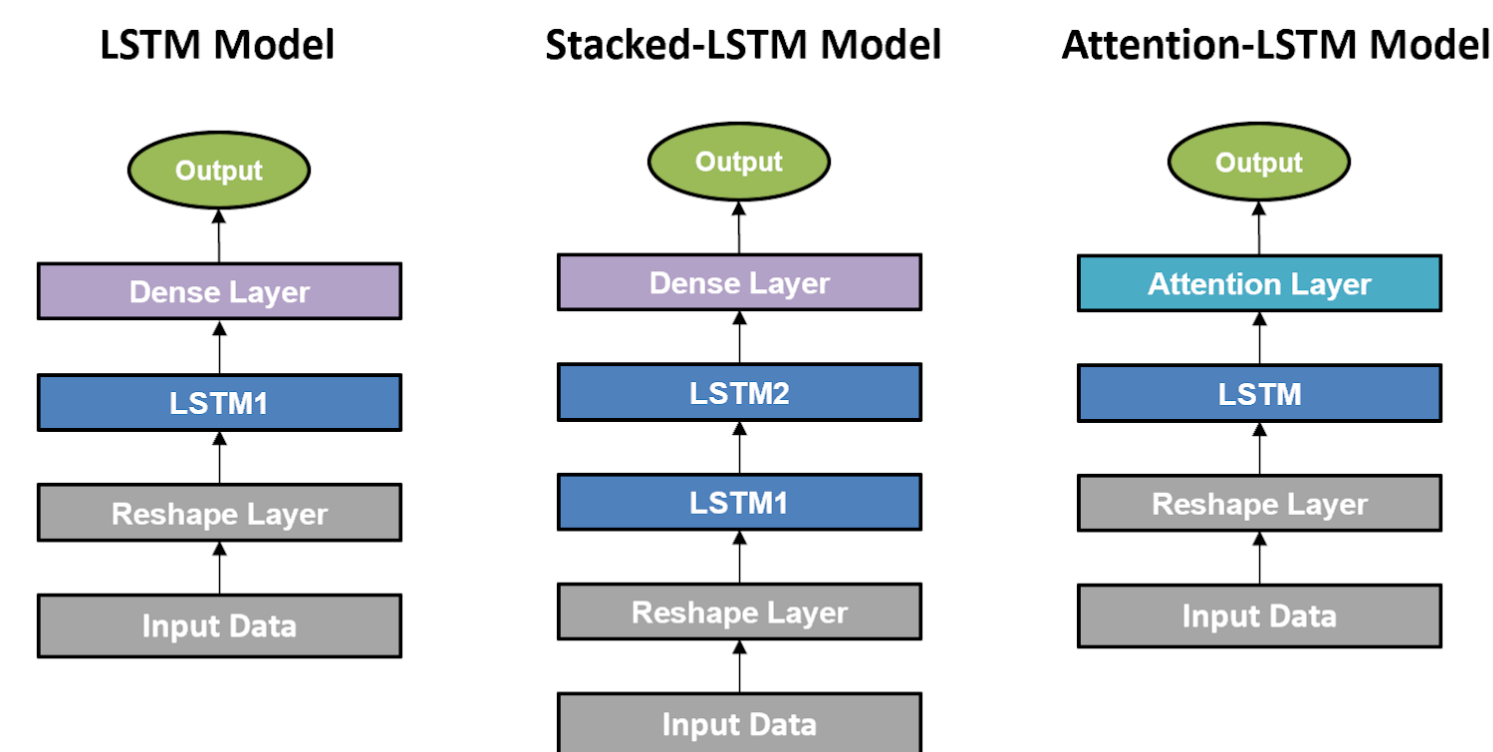


Figure 3. Illustration of three deep learning architects

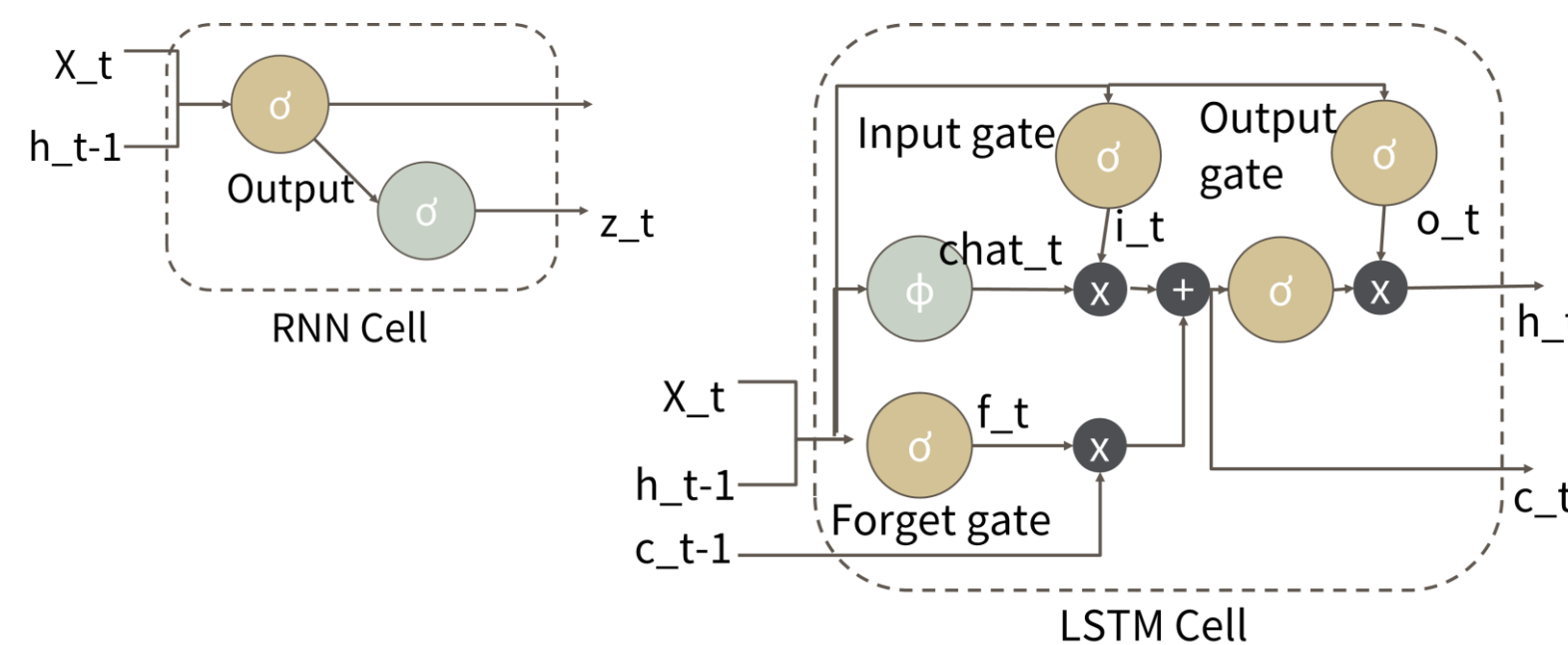


Figure 4. Illustration of typical RNN unit and LSTM unit

Besides prediction model, we also built two trading strategies to check the capability of gaining profit based on modelling results:

- Long-Only Strategy
- Long-Short Strategy

Two metrics were used to evaluate model performance:

- Mean-Squared-Error
- Total Annual Return on test set

## IV. Results

Mean-Squared-Error:

- ARIMA:  $(p, d, q) = (1, 0, 1)$ ,  $MSE = 0.0546$   
ARIMA didn't perform well on predicting non-linearity and long term results.
- Attention-LSTM outperformed among three deep learning models as expected.
- Single layer LSTM performed better than Stacked-LSTM

| Stock Ticker | Mean Squared Error ( $\times 10^{-3}$ ) |              |                |
|--------------|---|--------------|----------------|
|              | LSTM                                    | Stacked-LSTM | Attention-LSTM |
| XOM          | 25                                      | 25           | 11             |
| GE           | 18                                      | 2            | 3              |
| WMT          | 128                                     | 163          | 76             |
| MSFT         | 40                                      | 27           | 16             |
| IBM          | 28                                      | 7            | 6              |
| AAPL         | 54                                      | 61           | 44             |
| GOOG         | 35                                      | 37           | 26             |
| GS           | 12                                      | 16           | 18             |
| PFE          | 32                                      | 64           | 49             |
| JNJ          | 57                                      | 123          | 41             |

Figure 5. The summary of MSE on test set for three deep learning models.

Total Annual Return:

- Only Single-LSTM and Attention-LSTM were evaluated
- Both models significantly outperformed the benchmark

| Annual Return       | Trading Strategy Annual Return |                |           |
|---------------------|--------------------------------|----------------|-----------|
|                     | LSTM                           | Attention-LSTM | Benchmark |
| Long-Only Strategy  | 173%                           | 266%           | 30%       |
| Long-Short Strategy | 99%                            | 263%           | 30%       |

Figure 6. The summary of MSE on test set for three deep learning models.

## References

- Framework used: Keras, tensor flow.
- Toxic comment classification challenge, <https://www.kaggle.com/qjgeogor/keras-lstm-attention-glove840b-lb-0-043/log>.
- Ryo Akita, Akira Yoshihara, Takashi Matsubara, and Kuniaki Uehara. Deep learning for stock prediction using numerical and textual information. In *2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS)*, pages 1–6. IEEE, 2016.
- George EP Box, Gwilym M Jenkins, Gregory C Reinsel, and Greta M Ljung. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.
- JB Heaton, NG Polson, and Jan Hendrik Witte. Deep learning for finance: deep portfolios. *Applied Stochastic Models in Business and Industry*, 33(1):3–12, 2017.

## V. Discussion

- Attention-LSTM is the best:
  - A-LSTM brings the advantage of selecting the important and relevant information
  - Significant better performance on stocks which experienced large fluctuation, demonstrating the significance of relying on the context
  - The result of total annual return further emphasized the advantage of selecting most relevant info with the attention model
- Single-LSTM beats Stacked-LSTM
  - Opposite to our expectation as we assume complex architecture can learn non-linearity of stock trend better
  - Stacked-LSTM doesn't generalize well on unseen data
  - Stacked-LSTM is more suitable for predicting classification problems rather than continuous time series

## VI. Future Work

- Denosed data with Attention-LSTM: one difficulty of predicting stock arises from its non-stationary behavior, denoised data may improve the accuracy
- Incorporate high frequency data rather than quarterly reported statistics: one good example is the recent stock plunge due to COVID19, feeding timely info may help improve model performance.