



Long Short-Term Memory(LSTM)에서 시간 단위 민감도 분석을 통한 주가지수 예측

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Long Short-Term Memory(LSTM)에서 시간 단위 민감도 분석을 통한 주가지수 예측

UNIST

Song Donghwan, Moise Busogi, Namhun Kim

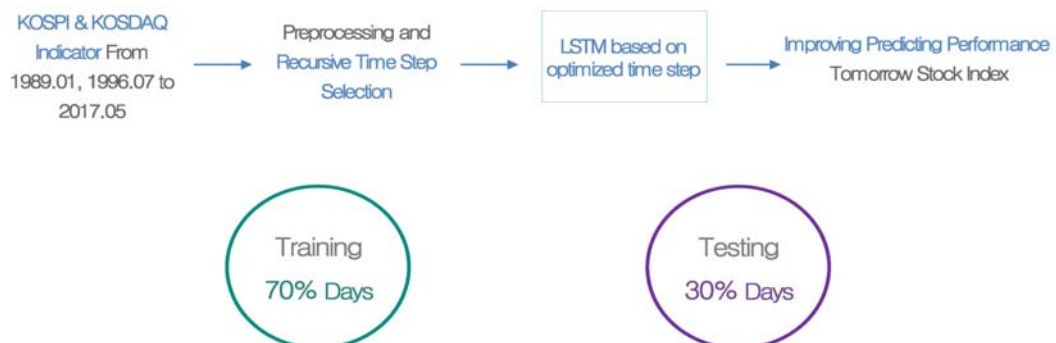
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Introduction Experiment Results Conclusion

Introduction

Key Concept

An adaptive time step adjustment method to enhance the performance of the LSTM algorithm for forecasting the stock index



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|---|---|
| Dataset Description | |
| Description | |
| Research Data : KOSPI INDEX | Research Data : KOSDAQ INDEX |
| Total sample : 7457 Trading days | Total sample : 5281 Trading days |
| From Jan 1989 to May 2017 | From July 1996 to May 2017 |
| 5220 (70%) – Training Data / 2237 (30%) – Test Data | 3697 (70%) – Training Data / 1584 (30%) – Test Data |
| Scaled into the range of [0, 1.0] – Min/Max Scaling | Scaled into the range of [0, 1.0] – Min/Max Scaling |
| Time Step : [5,10, … , 115, 120] | Time Step : [5,10, … , 115, 120] |
| Hidden Layer : 10 | Hidden Layer : 10 |
| Iteration : 5000 | Iteration : 5000 |
| Input Features : 7 (Open, High, Low, Close, Volume, Turnover, Diff) | Input Features : 7 (Open, High, Low, Close, Volume, Turnover, Diff) |
| Output Feature : 1 (Tomorrow KOSPI Index) | Output Feature : 1 (Tomorrow KOSDAQ Index) |

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Long short-term memory

The diagram illustrates the internal structure of an LSTM cell at time step t . It shows the flow of information between the previous cell ($Cell_{t-1}$), the current cell ($Cell_t$), and the next cell ($Cell_{t+1}$). The current cell receives an input vector x_t and the previous hidden state h_{t-1} and cell state c_{t-1} . Inside the cell, four gates are shown: the forget gate (f_t), the input gate (i_t), the cell state update gate (\tilde{c}_t), and the output gate (o_t). These gates are calculated using sigmoid (σ) and tanh activation functions. The cell state c_t is updated by multiplying the previous state by the forget gate and adding the product of the input gate and the new candidate state. The hidden state h_t is then calculated by passing the cell state through the output gate and a tanh activation function. The diagram also shows the flow of information to the next cell.

Fig. 1. Flow diagram including previous time step's cells in LSTM

$x_t = \{x_t^1, x_t^2, \dots, x_t^k\}$
 $i_t = \sigma(W_{xi} \cdot x_t^n + W_{hi} \cdot h_{t-1} + b_i)$
 $f_t = \sigma(W_{xf} \cdot x_t^n + W_{hf} \cdot h_{t-1} + b_f)$
 $o_t = \sigma(W_{xo} \cdot x_t^n + W_{ho} \cdot h_{t-1} + b_o)$

$: Input\ vector\ at\ t$
 $: Input\ gate$
 $: forget\ gate$
 $: output\ gate$

$\tilde{c}_t = \tanh(W_{cx} \cdot x_t^n + W_{ch} \cdot h_{t-1} + b_c)$
 $c_t = f_t * c_{t-1} + i_t * \tilde{c}_t$
 $h_t = o_t * \tanh(c_t)$

$: Sub\ Cell$
 $: New\ Cell$
 $: Output$

LSTM is a one of the most powerful algorithms for predicting timeseries data in deep learning

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Comparison Models

Support Vector Regression

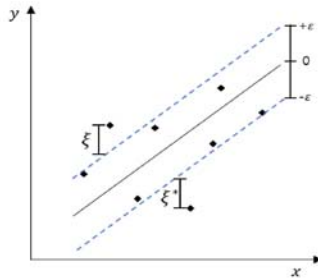


Fig. 2. Support Vector Regression with epsilon intensive band.

Artificial neural network

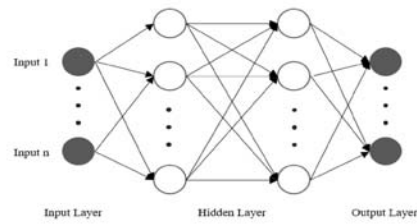


Fig. 3. Artificial neural networks model.

SVM, BPNN and Vanilla RNN are compared with t-LSTM

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Performance results for each time step

Performance Measures

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - f_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - f_i)^2}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - f_i}{y_i} \right|$$

Table1 Performance results of KOSPI and KOSDAQ for each time step

| Time Steps | K O S P I | | | K O S D A Q | | |
|------------|-----------|--------|-------|-------------|--------|-------|
| | MAE | RMSE | MAPE | MAE | RMSE | MAPE |
| 5 | 17.627 | 23.254 | 0.992 | 6.533 | 9.921 | 1.102 |
| 10 | 16.613 | 22.323 | 0.943 | 5.977 | 8.210 | 1.033 |
| 15 | 16.418 | 22.131 | 0.935 | 5.561 | 7.858 | 0.969 |
| 20 | 16.251 | 21.974 | 0.930 | 5.988 | 8.515 | 1.029 |
| 25 | 16.416 | 21.999 | 0.933 | 6.519 | 9.229 | 1.109 |
| 30 | 16.726 | 22.248 | 0.948 | 6.634 | 9.506 | 1.127 |
| 35 | 17.192 | 22.665 | 0.970 | 6.960 | 9.996 | 1.178 |
| 40 | 17.339 | 22.803 | 0.978 | 7.097 | 10.186 | 1.200 |
| 45 | 17.594 | 23.028 | 0.990 | 7.283 | 10.450 | 1.230 |
| 50 | 17.639 | 23.072 | 0.992 | 7.352 | 10.540 | 1.241 |
| 55 | 17.633 | 23.073 | 0.992 | 7.294 | 10.438 | 1.232 |
| 60 | 17.728 | 23.162 | 0.996 | 7.368 | 10.547 | 1.244 |
| 65 | 17.861 | 23.286 | 1.003 | 7.403 | 10.594 | 1.249 |
| 70 | 17.875 | 23.297 | 1.004 | 7.474 | 10.700 | 1.260 |
| 75 | 17.842 | 23.266 | 1.002 | 7.437 | 10.633 | 1.255 |
| 80 | 17.993 | 23.405 | 1.009 | 7.482 | 10.699 | 1.262 |
| 85 | 18.070 | 23.473 | 1.013 | 7.418 | 10.605 | 1.252 |
| 90 | 18.219 | 23.603 | 1.020 | 7.537 | 10.781 | 1.270 |
| 95 | 18.318 | 23.687 | 1.025 | 7.484 | 10.695 | 1.262 |
| 100 | 18.324 | 23.693 | 1.025 | 7.525 | 10.759 | 1.268 |
| 105 | 18.306 | 23.673 | 1.024 | 7.576 | 10.828 | 1.276 |
| 110 | 18.320 | 23.687 | 1.024 | 7.621 | 10.895 | 1.283 |
| 115 | 18.367 | 23.735 | 1.026 | 7.508 | 10.719 | 1.266 |
| 120 | 18.317 | 23.693 | 1.024 | 7.554 | 10.788 | 1.273 |

Table 2 Comparison table of t-LSTM and other algorithms

| | K O S P I | | | K O S D A Q | | |
|--------|-----------|--------|-------|-------------|--------|-------|
| | MAE | RMSE | MAPE | MAE | RMSE | MAPE |
| t-LSTM | 16.351 | 21.974 | 0.930 | 5.561 | 7.858 | 0.969 |
| RNN | 17.084 | 22.500 | 0.963 | 6.431 | 8.563 | 1.116 |
| BPN | 64.790 | 22.834 | 0.940 | 5.530 | 9.973 | 3.730 |
| SVR | 53.026 | 59.008 | 2.812 | 31.977 | 35.651 | 5.682 |

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Error Graph for each time steps

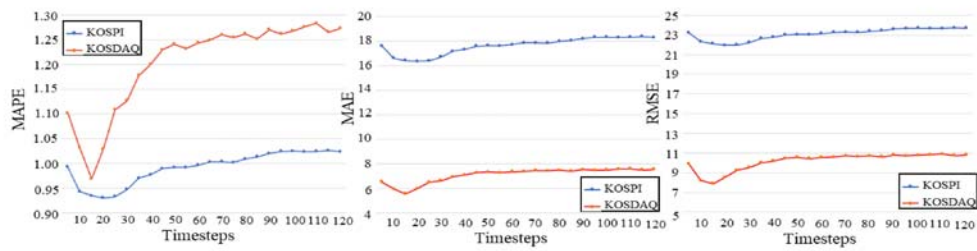


Fig. 4. MAPE, MAE and RMSE measured at each time step in the prediction of KOSPI and KOSDAQ indices using LSTM

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Comparison Results

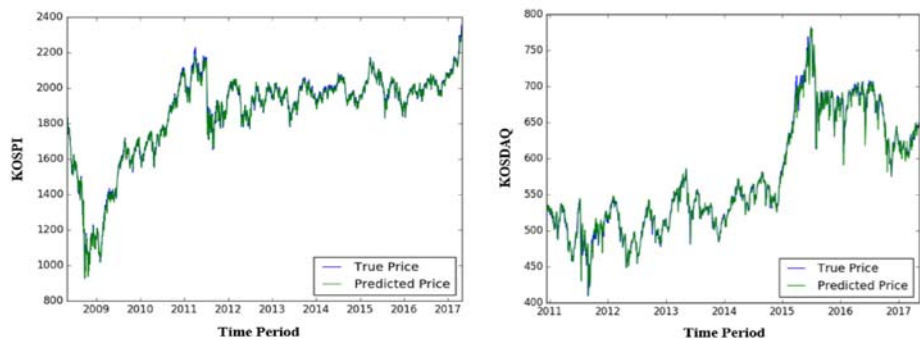


Fig. 5. Comparison predicted price with test period for each Index

Back-Testing Simulation

Back Testing Strategy

$$P_t = \frac{\tilde{Y}_t - Y_t}{Y_t} * 100$$

$1.5 < P_t < 2$: buy 100%
 $1 < P_t < 1.5$: buy 90%
 $0.5 < P_t < 1$: buy 80%
 $0 < P_t < 0.5$: buy 50%
 $-0.5 < P_t < 0$: sell 50%
 $-1 < P_t < -0.5$: sell 80%
 $-1.5 < P_t < -1$: sell 90%
 $-2 < P_t < -1.5$: sell 100%

in current portfolio capital

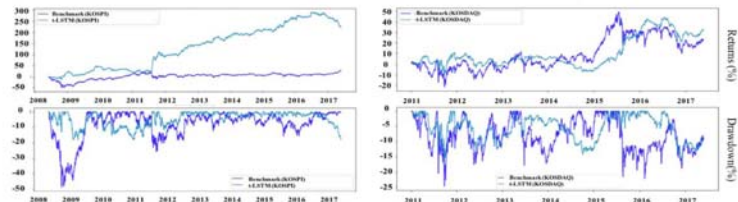


Fig. 6. t-LSTM Simulation results about Returns and Drawdown for KOSPI and KOSDAQ

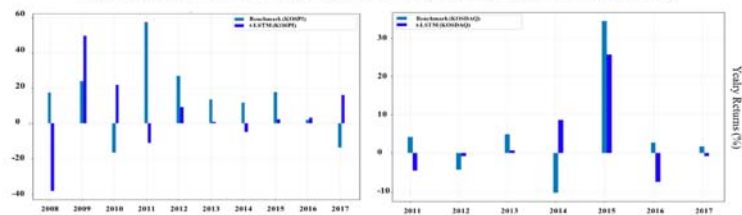


Fig. 7. t-LSTM simulation results about Yearly Returns for KOSPI and KOSDAQ

Back-Testing Results and Extended Analysis

Table 3 Back-testing Simulation result for each index

| | t-LSTM(KOSPI) | Benchmark(KOSPI) | t-LSTM(KOSDAQ) | Benchmark(KOSDAQ) |
|--------------|---------------|------------------|----------------|-------------------|
| Total Return | 220.96% | 29.33% | 32.05% | 19.59% |
| CAGR | 14.08% | 2.95% | 4.54% | 2.89% |
| Volatility | 18.99% | 14.21% | 14.99% | 11.8% |
| Sharp Ratio | 99.64% | 48.25% | 39.35% | 48.33% |
| MDD | -18.25% | -48.81% | -16.86% | -24.77% |

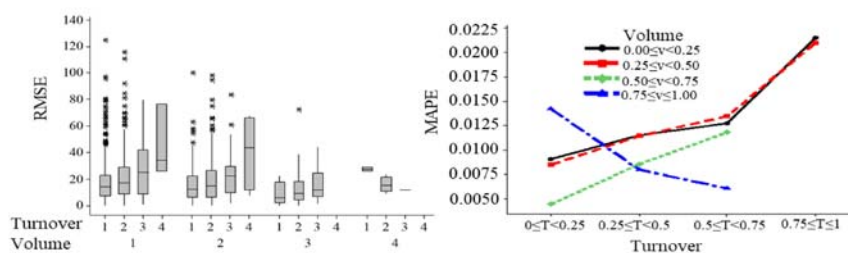


Fig. 8. Prediction error according to turnover and volume.

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Summary & Conclusion

Conclusion

- The presented **t-LSTM performs better** than simple RNN, BPN or SVR.
- LSTM performs the best (i.e., predicting the closing price using KOSPI and KOSDAQ) when the time step is approximately set between **three weeks (15 actual trading days)** and **four weeks (20 actual trading days)**.
- The optimal time step of KOSDAQ is expected to be shorter than that of KOSPI, and it implies **KOSDAQ is more sensitive to recent information than KOSPI**.
- According to the experimental results, KOSDAQ changes at a higher rate than KOSPI as the time step interval changes; therefore, **the KOSDAQ has greater volatility than the KOSPI**.
- Recall that in both KOSPI and KOSDAQ, **the prediction performance worsens as the time step increases beyond the optimal point**. Hence, it is imperative to set a more appropriate time step value, rather than setting an arbitrary value as the length of the memory cell in LSTM.
- **The performance of t-LSTM with proper adjustment is superior** to the benchmark index in returns and risk management.

Thank You