# Attention LSTM for time series prediction 구현 및 실험 결과 보고

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# Introduction

- Encoder-Decoder lstm 에서 발전한 형태로 Attention 이라는 개념을 도입.
- Decoder의 각 시점에서, Encoder의 시점별 중요도를 반영.
- RNN구조의 정보 손실을 보완.

# Related works

- Attention lstm structure

  - Decoder hidden state

$$s_t \in \mathbb{R}^h$$

  - Attention socre

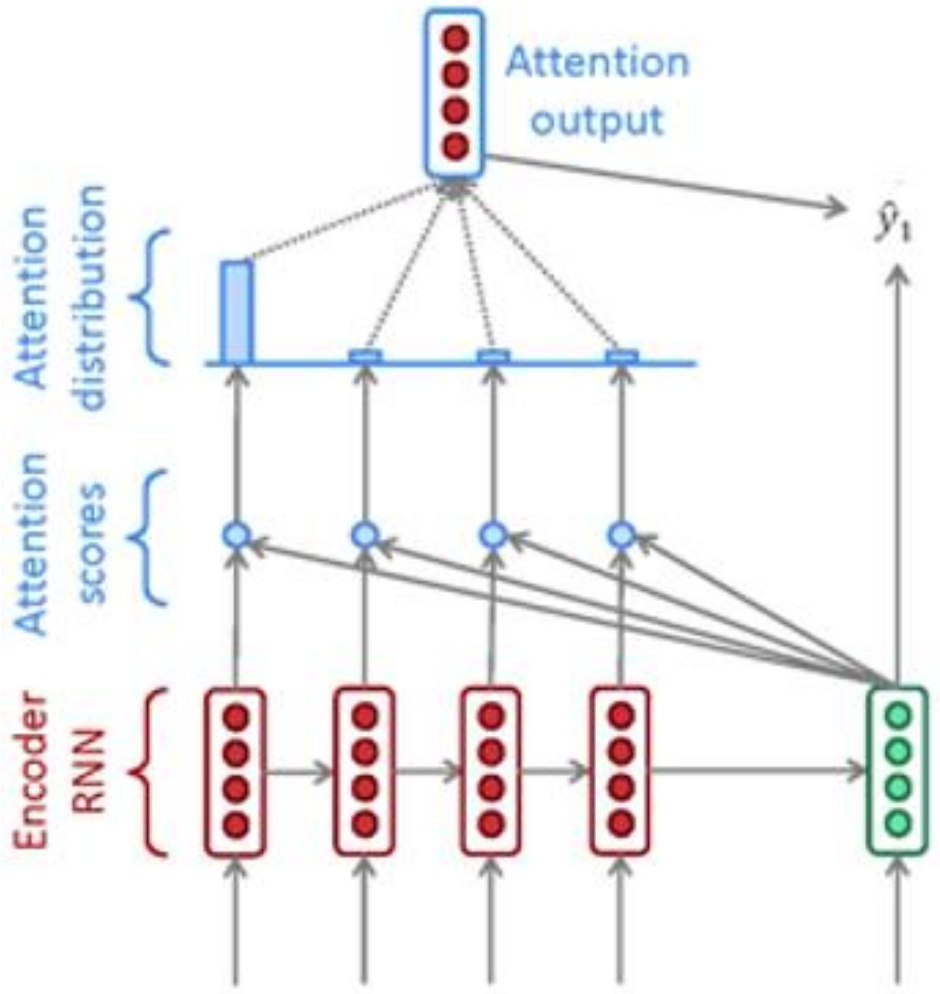
$$e^t = [s_t^T h_1, \dots, s_t^T h_N] \in \mathbb{R}^N$$

  - Attention distiribution

$$\alpha^t = \mathrm{softmax}(e^t) \in \mathbb{R}^N$$

  - Weighted sum

$$a_t = \sum_{i=1}^{N} \alpha_i^t h_i \in \mathbb{R}^h$$



# Related works

- Stock data Normalization

| 학회 명 | 논문 명 | 발간 년도 | 인용 수 | normalization 방식 | normalization 범위 | 실제 내용 |
|---|---|---|---|---|---|---|
| Expert Systems With Applications | ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module | 2018 | 80 | min-max normalization | 언급 x | where X is original value at a data point, X max and X min are maximum and minimum value of a specific feature, respectively. Consequently, every feature change could be captured in the range of [0,1]. |
| Expert Systems with Applications | Stock price prediction using deep learning and frequency decomposition | 2020 | 1 | min-max normalization | 언급 x | After decomposition of indices into various frequency spectra, it is required to convert the original data to normal data before training. Normalization leads to the adjustment of the data noise effect and implementation of neural networks with high efficiency and speed (Makridakis, 1993; Diehl, et al., 2015). To this end, we use the following equation. |
| IEEE ACCESS | Multivariate Financial Time-Series Prediction With Certified Robustness | 2020 | 2 | min-max normalization | 언급 x | To detect the agricultural commodity futures price pattern, it is necessary to normalize the agricultural commodity futures price data. Since the LSTM neural network requires the agricultural commodity futures patterns during training, we use the ``min-max'' normalization method to reform dataset, which keeps the pattern of the data, as follow: |
| Quantitative Bio-Science | Forecasting the KOSPI 200 Stock Index Based on LSTM Autoencoder | 2020 | 0 | batch normalization | 언급 x | batch normalization was added to the model, and early stopping in Keras's callback functions was utilized. For the loss function and the optimization function, both the autoencoder and the predictive model used MSE (Mean-Squared-Error) and Adam Optimizer. |
| International Journal of Machine Learning and Cybernetics | Study on the prediction of stock price based on the associated network model of LSTM | 2020 | 20 | min-max normalization | 언급 x | Due to the different measurement unit of different stock index data, for avoiding the impact of different measurement unit, all the attribute data are normalized to fall within a same range. In this paper, the min–max normalization method is used. The normalization function is shown in Eq. 11 |

# Related works

- Stock data Normalization

| 학회 명 | 논문 명 | 발간 년도 | 인용 수 | normalization 방식 | normalization 범위 | 실제 내용 |
|---|---|---|---|---|---|---|
| IEEE ACCESS | Feature Engineering for Mid-Price Prediction With Deep Learning | 2019 | 18 | min-max normalization | 전체 데이터에 적용 | The next step of the pre-processing step is data normalization. We perform a filtering and a normalization method during the feature extraction process and training. The first one is a statistical filtering method , while the second one is based on MinMax. More specifically, we perform the filtering methodology first and apply it directly on the raw MB data. The main idea of the methodology is to identify and eliminate any observation that does not reflect market activity. |
| Neural Computing and Applications | Stock price prediction based on deep neural networks | 2019 | 43 | min-max normalization | 언급 x | To facilitate better observation and comparison of the experimental results, PSR, de-noising and normalization were first performed in the model parameter experiment. |
| Proceedings of Machine Learning Research | Stock Price Prediction Using Attention-based Multi-Input LSTM | 2018 | 33 | min-max normalization | 언급 x | Notice that the MSE we calculated are derived from normalized data. That's because there exists huge value gap among different stocks. If we use original stock price to evaluate error, the error of high price stocks would probably be much more larger than low price ones, which implies models perform better on high price stocks would very likely to have better overall performance. Thus the performance on low price stocks would become dispensable. To avoid the bias caused by the aforementioned problem we evaluate the error with normalized stock price ranged from -1 to 1. |
| IEEE | Hybrid Deep Learning Model for Stock Price Prediction | 2018 | 18 | min-max normalization | 전체 데이터에 적용 | we present the normalized training data form 1950 to 2002. The curve shows the randomness of stock price data. Our main goal is to predict the closing price of next day. We put all the training data into a one dimensional vector and pass it to the network with a fixed learning rate(.001). Figure 6 shows the normalized test dataset representation, which is also showing the randomness of stock price. |

# Related works

- Stock data Normalization

| 학회 명 | 논문 명 | 발간 년도 | 인용 수 | normalization 방식 | normalization 범위 | 실제 내용 |
|---|---|---|---|---|---|---|
| Physica A: Statistical Mechanics and its Applications | Financial time series forecasting model based on CEEMDAN and LSTM | 2018 | 111 | min-max normalization | 전체 데이터에 적용 | Where minx(t) and maxx(t) are the minimum and maximum value of the whole time series respectively. |
| International Conference on Advances in Computing, Communications and Informatics (ICACCI) | STOCK PRICE PREDICTION USING LSTM,RNN AND CNN-SLIDING WINDOW MODEL | 2017 | 235 | min-max normalization | 언급 x | The data varies with in a range of 2000 to 4000 for Infosys and TCS and for Cipla it is 400 to 700. To unify the data range, it was subjected to normalization and was mapped to a range of 0 to 1. This normalized data was given to the network for training. |
| IEEE International Conference On Recent Trends in Electronics Information & Communication Technology (RTEICT) | Short Term Stock Price Prediction Using Deep Learning | 2017 | 41 | min-max normalization | 언급 x | The data of each stock consists of approximately 85000 – 90000 points. The data was normalized into the range of [0, 1] using MinMaxScaler(2), since neural networks are known to be sensitive to unnormalized data, which is then fed to the prediction model. |
| IEEE International Conference on Big Data | A LSTM-based method for stock returns prediction : A case study of China stock market | 2015 | 286 | mean and standard deviation | 각각의 seqence vector에 적용 | normalization was applied for each vector of a sequence by using the mean and standard deviation of each stock computed from the training set. |
| International Conference on Business Analytics and Intelligence | Stock Price Prediction Using Machine Learning and Deep Learning Frameworks | 2018 | 19 | min-max normalization | 전체 데이터에 적용 | The raw data is normalized using the min-max normalization |
| Expert Systems With Applications | ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module | 2018 | 80 | min-max normalization | 전체 데이터에 적용 | X max and X min are max- imum and minimum value of a specific feature, |

# Related works

- Investment stratege

– normalization applied to each split sequence

“normalization was applied for each vector of a sequence by using”, A LSTM-based method for stock returns prediction : A case study of China stock market (2015)

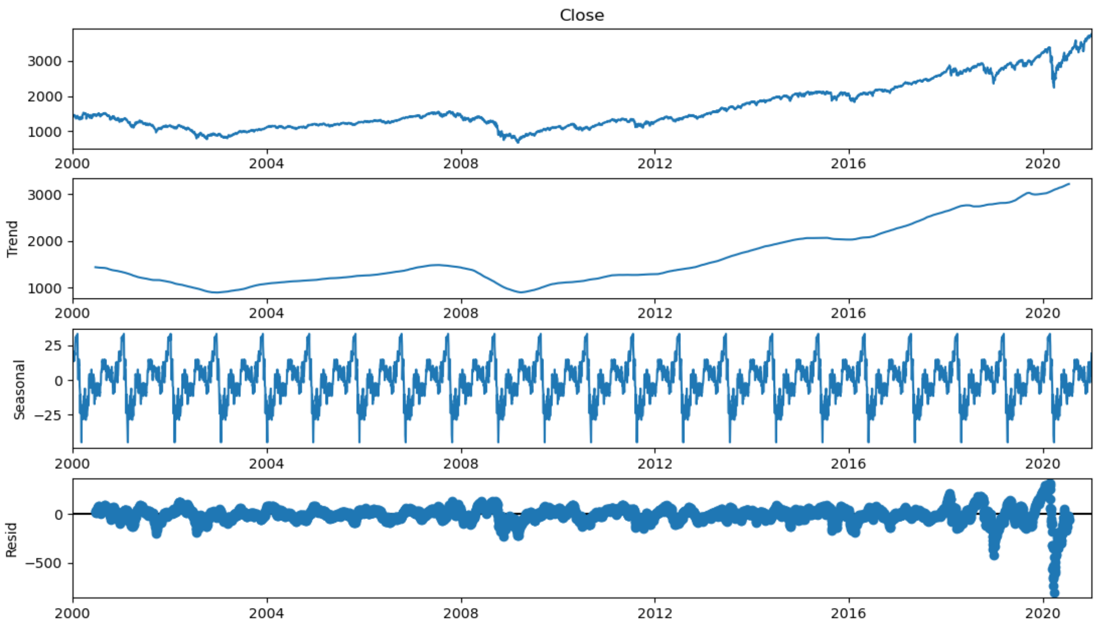
– normalization applied to entire sequence

“The raw data is normalized using the min-max normalization”, Stock Price Prediction Using Machine Learning and Deep Learning Frameworks

>> In the result of an experiment, normalization applied to each split sequence shows better performance than normalization applied to entire sequence

# Related works

- Time series decomposition (S&P 500 Index)




1) 기존의 데이터를 이동평균을 이용하여 Trend를 계산
(이동평균의 개수는 freqency를 그래프를 보고 지정)

2) 전체 데이터에서 계산된 Trend를 뺀 후 지정된 frequency 만큼의 term을 뒤 평균을 낸 값을 seasonal로 사용.

3) (Raw data) – (seasonal) – (trend) = Residual

>> 추출된 Residual을 arima등 전통적인 시계열 예측을 위해 정상시계열(Stationary)로 만드는데 사용됨

>> frequency를 지정해줘야함.

# Related works

- 주식 가격의 노이즈 제거 및 분해를 위해 사용되는 방식.
  - STL(Seasonal and Trend decomposition using Loess)
    - loess regression을 이용
      1) 적합한 근사 추세선을 찾는다.
      2) 추세이탈 시계열에서 seasonal 시계열을 찾는다.
      3) De-seasonalised data에서 다항회귀를 적용한다.

A novel hybrid model based on STL decomposition and one-dimensional convolutional neural networks with positional encoding for significant wave height forecast, ShaoboYang, ZeguiDeng,XingfeiLi, ChongweiZheng, LintongXi, JuchengZhuang, ZhenquanZhang, ZhiyouZhang, RENEWABLE ENERGY(2021), SCIE, IF 5.439

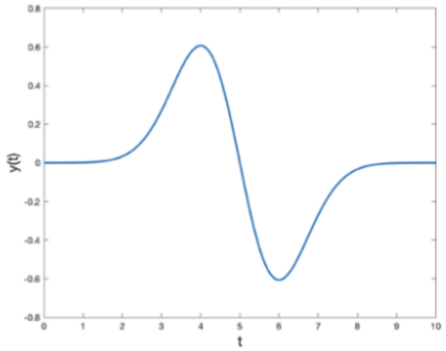
# Related works

- 주식 가격의 노이즈 제거 및 분해를 위해 사용되는 방식.

– Wavelet Transform

  – global frequency information를 포착하는 Fourier Transform의 대안으로 사용됨

  – 우측의 그림과 같은 파형을 생성해 위치를 옮겨가며
    convolution 연산을 시켜주면 계수를 얻을 수 있고,
   얻어진 계수로 wavelet scale 을 증가시고 해당 과정을 반복함.




**Electricity price prediction based on hybrid model of adam optimized LSTM neural network and wavelet transform, ZihanChang, YangZhang, WenboChen, Energy (2019), SCIE, 6.082**

# Related works

- 주식 가격의 노이즈 제거 및 분해를 위해 사용되는 방식.

  - Empirical Mode Decomposition(EMD) – (Hilbert–Huang transform)

    - EMD는 raw series를 n개의 IMF(Intrinsic mode functions, 고유진동함수)들과 residual로 분해한다.

    - Parameter를 정의할 필요가 없다.

    - EMD는 비선형(non-linear), 비정상(non-stationary) 시계열에 적용이 가능한 시공간 분석 방법(time-space analysis method)이다.

**Hybrid deep learning predictor for smart agriculture sensing based on empirical mode decomposition and gated recurrent unit group model, XB Jin, NX Yang, XY Wang, YT Bai, TL Su, JL Kong , Sensors, (2020), SCIE, IF 3.275**

# Related works

- 최근 동향

| 학회 명 | | IF | 논문 명 | 발간 년도 | 인용 수 | 내용 |
|---|---|---|---|---|---|---|
| IEEE ACCESS | SCIE | 3.7 | A Prediction Approach for Stock Market Vo latility Based on Time Series Data | 2019 | 48 | 전통적인 통계적 방식을 이용한 시계열 예측의 개요 |
| International Conf erence on Big Dat a | | 0.75 | Applied attention-based LSTM neural netw orks in stock prediction | 2018 | 22 | Attention mechanism을 이용한 주식 가격 예측 |
| Expert Systems Wi th Applications | SCIE | 8.67 | CNNpred: CNN-base d stock market predi ction using a diverse set of variables<br>Related work | 2019 | 79 | Cnn을 이용하여 Automatic fe ature selection과 예측 목적과 다른 주변 주식시장을 데이터로 이용하여 주식가격 예측 |
| ENTROPY | SCIE | 3.01 | Deep Learning for Stock Market Prediction | 2020 | 127 | 금융시장, 석유, 비금속광물, 광물의 미래 가격을 RNN계열과, 머신러닝 방법으로 예측 |
| Quantitative Finance | SCIE | 2.77 | Exploring the attention mechanism in LST M-based Hong Kong stock price moveme nt prediction | 2019 | 19 | Attention 구조를 이용한 주식 가격 예측 |
| PLOS ONE | SCIE | 3.04 | Forecasting stock prices with long-short term memory neural network based on attention mechanism | 2020 | 51 | LSTM을 이용하여 Wavelet tra nsform, attention mechanism을 적용하여 주가예측 |

# Related works

- 최근 동향

| 학회 명 | | IF | 논문 명 | 발간 년도 | 인용 수 | 내용 |
|---|---|---|---|---|---|---|
| NEURAL COMPUTATION | SCIE | 3.47 | Improving Stock Closing Price Prediction Using Recurrent Neural Network and Technical Indicators | 2018 | 27 | 주식시장의 기술적 지표(종가, 시가, 거래량 등) 15개 데이터를 pca를 통하여 전처리 후 lstm을 이용하여 예측 |
| Procedia Computer Science | | 2.09 | Stock Market Prediction Based on Generative Adversarial Network | 2019 | 58 | Generative Adversarial Network가 종가 예측에 뛰어난 성능을 보임 |
| Materials Science and Engineering | | 5.88 | Stock Prediction Using Convolutional Neural Network | 2018 | 28 | Convolutional Neural Network을 사용하여 주가 예측 |
| Proceedings of The 10th Asian Conference on Machine Learning, PMLR | | | Stock Price Prediction Using Attention-based Multi-Input LSTM | 2018 | 38 | Index를 포함해 negative, positive값을 추가해 attention mechnism에 적용 |
| Expert Systems With Applications | SCIE | 8.67 | Stock price prediction using deep learning and frequency decomposition | 2021 | 5 | frequency decomposition (CEEMD)을 이용하여 CNN-LSTM을 결합한 모델을 이용하여 주가 예측 |
| IEEE TRANSACTIONS ON FUZZY SYSTEMS | SCIE | 8.759 | Multiobjective Evolution of Fuzzy Rough Neural Network via Distributed Parallelism for Stock Prediction | 2020 | 92 | Fuzzy rough theory, parallel<br>Multiobjective evolutionary algorithms을 이용하여 computational time을 감소시켰다. |

# Experimental setting

- Data normalization
  - min-max normalization

- Loss function
  - Used MSE Loss as loss function

- Optimizer
  - Adam

- Metric
  - $\mathrm{MAE}(e^{predicted\ value}, e^{true\ value})$
  - $\mathrm{RMSE}(e^{predicted\ value}, e^{true\ value})$
  - $\mathrm{MAPE}(e^{predicted\ value}, e^{true\ value})$

| **Hyperparameters** | **Number** |
|---|---|
| hidden state, cell state dimension | 10 |
| input sequence length | 20 |
| output sequence length | 1 |
| epoch | 120 |
| Batch size | 128 |

# Experimental setting

- To determine the detailed performance of a model
  - Add another model evaluation metric.

    - Mean Absolute Percentage Error (MAPE) = $\frac{\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right|}{n} \cdot 100(\%)$

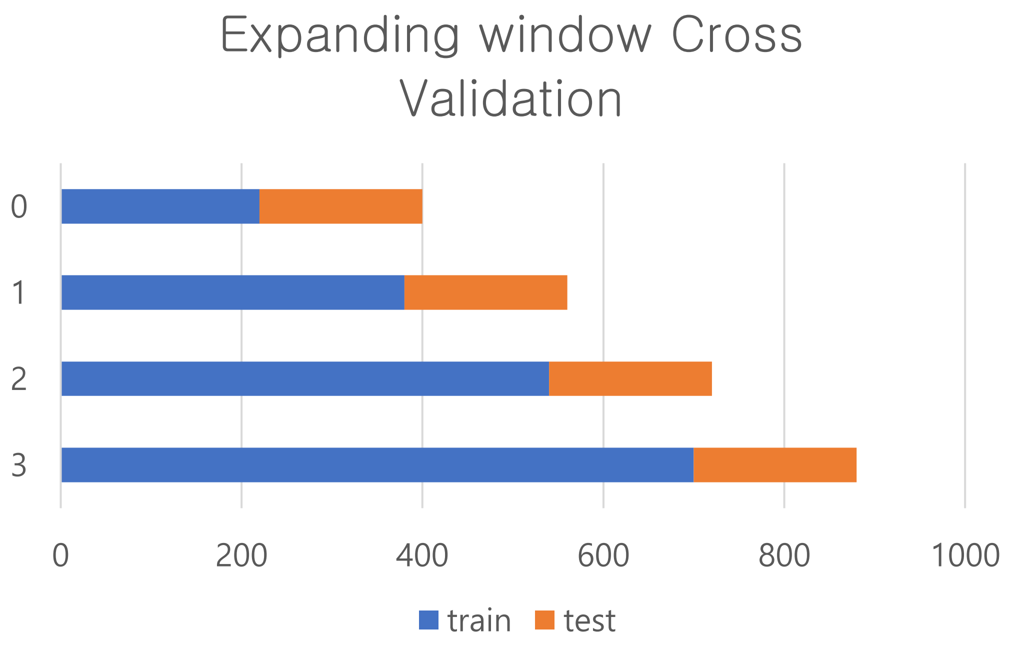
      - MAPE is undefined for data points where the value is zero.
      - MAPE is biased towards prediction that are systemically less than the actual values themselves

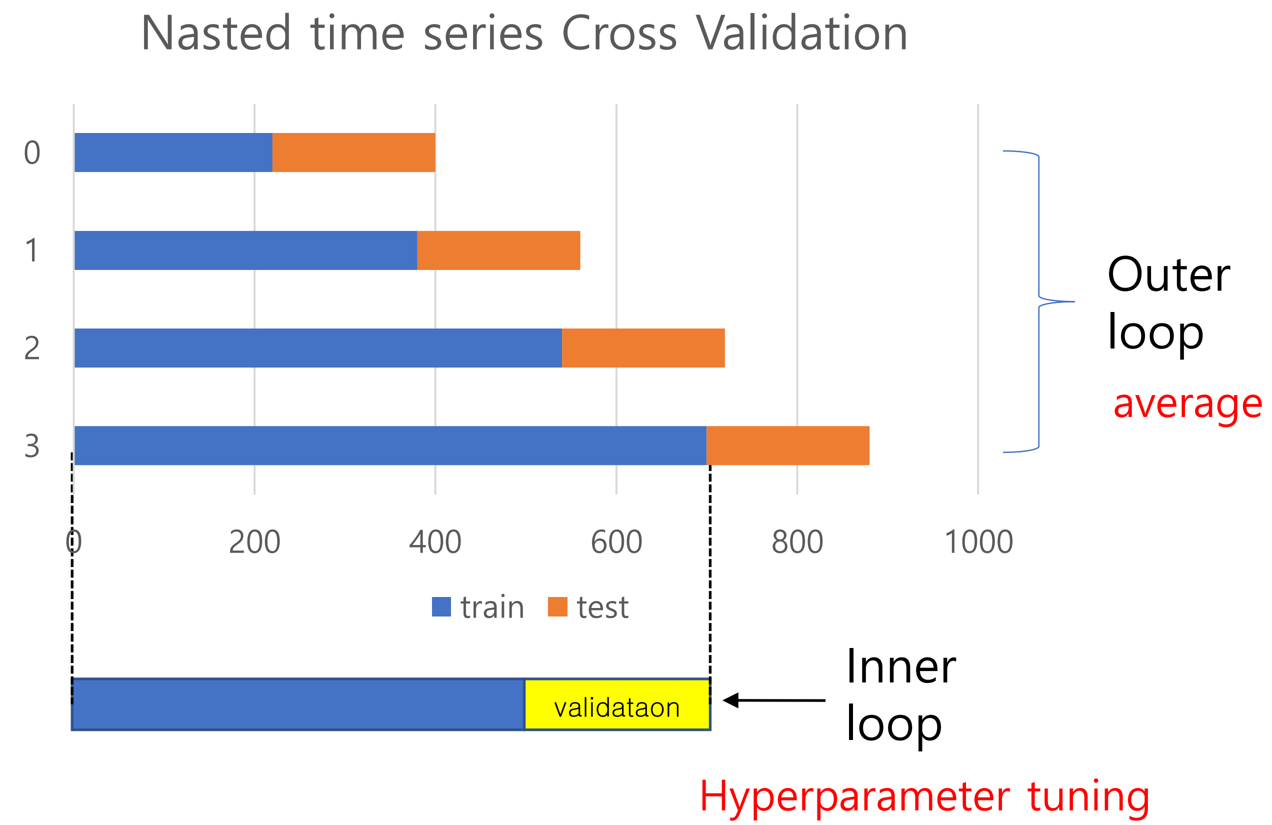
$$y = 20, \hat{y} = 10, n = 1 \ \rightarrow MAPE = 50\%$$
$$y = 10, \hat{y} = 20, n = 1 \ \rightarrow MAPE = 100\%$$

  - Compare three metrics.
    - MAE
    - RMSE
    - MAPE

# Experimental setting

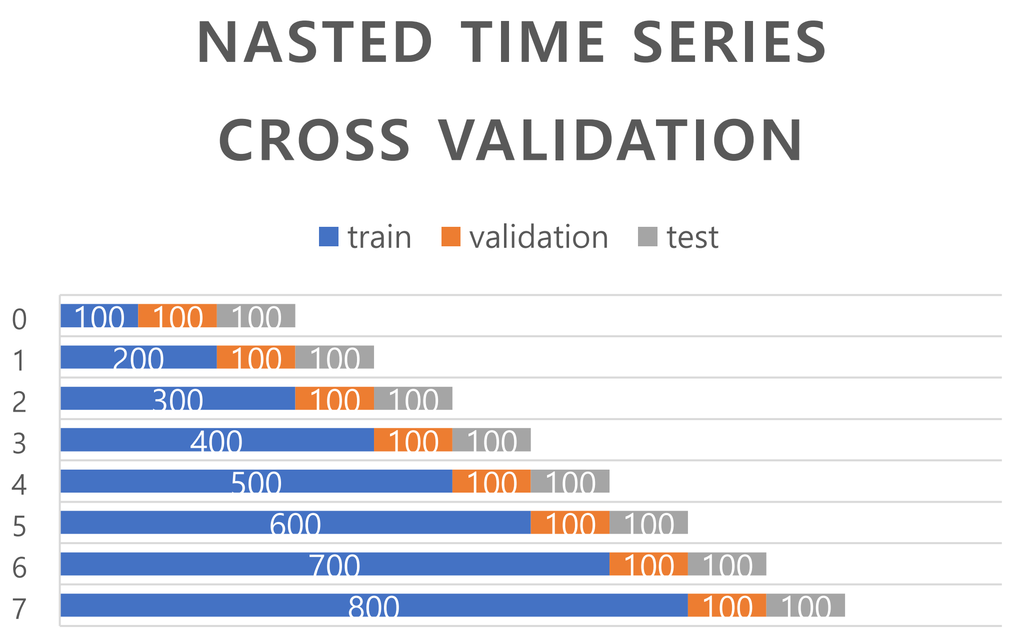
- Stock dataset split in timeseries data



# Experimental setting

- Nasted time series Cross Validation




Train : validataion : test = 8 : 1 : 1

- Maximum iteration is 8
- Iteration from 3 to 5 is used universally in timeseries data cross-validtaion.

\- More data should be collected.

# Comparison results

- Mean Absolute Error (Normalized to each sequence)

| Data | Proposed | Standard Deviation | RNN | Standard Deviation | LSTM | Standard Deviation | GRU | Standard Deviation | Enc-Dec LSTM | Standard Deviation |
|---|---|---|---|---|---|---|---|---|---|---|
| 네덜란드 AEX(^AEX) | | | 9.700 | 4.321 | **9.072 | 2.430 | 12.169 | 5.305 | 9.249 | 3.630 |
| 인도 선섹스(^BSESN) | | | 522.481 | 143.644 | 757.710 | 311.438 | 635.134 | 240.285 | **409.767 | 121.605 |
| 브라질 보베스파(^BVSP) | | | 1531.036 | 549.161 | **1529.299 | 754.228 | 2040.192 | 650.570 | 2188.410 | 748.355 |
| 다우존스(^DJI) | | | **379.666 | 155.520 | 386.981 | 130.981 | 383.127 | 141.125 | 438.104 | 263.496 |
| 프랑스 CAC(^FCHI) | | | 132.848 | 64.138 | 114.632 | 47.652 | **86.384 | 43.260 | 110.651 | 51.728 |
| 독일 DAX(^GDAXI) | | | 287.096 | 174.637 | **236.222 | 97.034 | 276.421 | 131.694 | 283.876 | 112.716 |
| S&P 500(^GSPC) | | | 45.127 | 28.311 | 40.281 | 20.761 | **33.122 | 14.978 | 42.765 | 21.438 |
| 홍콩 항생(^HSI) | | | 625.978 | 235.568 | **464.189 | 119.809 | 592.841 | 292.263 | 562.736 | 159.684 |
| 스페인 IBEX(^IBEX) | | | 223.378 | 159.649 | **222.907 | 108.678 | 245.819 | 167.813 | 235.776 | 104.426 |
| NASDAQ(^IXIC) | | | **109.496 | 46.546 | 122.264 | 41.803 | 126.881 | 49.249 | 157.227 | 69.242 |
| KOSDAQ(^KQ11) | | | 27.665 | 9.407 | 25.220 | 14.498 | **23.798 | 11.050 | 23.851 | 10.023 |
| KOSPI(^KS11) | | | 35.608 | 13.477 | 39.714 | 13.813 | **31.784 | 11.158 | 35.751 | 16.443 |
| 일본 니케이(^N225) | | | 537.349 | 282.333 | **482.213 | 198.073 | 539.397 | 336.067 | 692.156 | 356.340 |
| 대만 기권(^TWII) | | | 159.542 | 66.302 | 172.253 | 62.575 | 157.141 | 58.127 | **135.595 | 61.697 |
| 비트코인 암호화폐(BTC-USD) | | | 419.973 | 274.202 | **325.423 | 249.265 | 542.294 | 699.560 | 559.299 | 763.136 |
| Oil price(CL=F) | | | 2.953 | 1.809 | **1.990 | 0.913 | 2.678 | 2.093 | 2.325 | 1.501 |
| 이더리움 암호화폐(ETH-USD) | | | 40.476 | 33.185 | 28.455 | 21.580 | **27.205 | 21.683 | 42.154 | 33.436 |
| Gold price(GC=F) | | | 21.052 | 12.822 | **20.112 | 14.340 | 22.077 | 14.279 | 27.564 | 12.884 |

R Vinayakumar; E. A Gopalakrishnan; Vijay Krishna Menon; K. P. Soman, Stock price prediction using LSTM, RNN and CNN-sliding window model, **ICACCI**(2017), IF 1.00

# Comparison results

- Root Mean Squared Error (Normalized to each sequence)

| Data | Proposed | Standard Deviation | RNN | Standard Deviation | LSTM | Standard Deviation | GRU | Standard Deviation | Enc-Dec LSTM | Standard Deviation |
|---|---|---|---|---|---|---|---|---|---|---|
| 네덜란드 AEX(^AEX) | | | 11.304 | 5.039 | **10.566 | 3.010 | 14.227 | 6.222 | 10.572 | 3.943 |
| 인도 선섹스(^BSESN) | | | 625.698 | 182.463 | 869.819 | 402.124 | 727.703 | 268.761 | **506.799 | 170.489 |
| 브라질 보베스파(^BVSP) | | | 1858.968 | 676.142 | **1829.228 | 913.358 | 2366.848 | 728.495 | 2558.670 | 883.479 |
| 다우존스(^DJI) | | | 451.991 | 207.007 | **447.909 | 167.888 | 449.206 | 177.294 | 517.604 | 345.870 |
| 프랑스 CAC(^FCHI) | | | 154.815 | 76.128 | 132.486 | 56.154 | **102.502 | 47.582 | 131.174 | 64.944 |
| 독일 DAX(^GDAXI) | | | 339.719 | 193.275 | **274.045 | 103.857 | 319.372 | 161.814 | 328.517 | 124.275 |
| S&P 500(^GSPC) | | | 52.531 | 35.028 | 47.002 | 25.976 | **39.627 | 19.338 | 49.762 | 25.417 |
| 홍콩 항생(^HSI) | | | 751.627 | 282.089 | **540.112 | 120.722 | 687.794 | 313.541 | 671.273 | 197.581 |
| 스페인 IBEX(^IBEX) | | | 262.575 | 175.966 | **256.591 | 116.325 | 278.552 | 174.035 | 275.532 | 119.596 |
| NASDAQ(^IXIC) | | | **127.552 | 57.086 | 144.600 | 50.219 | 147.346 | 57.546 | 177.893 | 77.217 |
| KOSDAQ(^KQ11) | | | 31.153 | 9.875 | 29.395 | 16.572 | **27.159 | 11.997 | 27.257 | 10.410 |
| KOSPI(^KS11) | | | 41.436 | 14.432 | 44.939 | 14.383 | **37.307 | 13.317 | 42.370 | 18.105 |
| 일본 니케이(^N225) | | | 610.658 | 288.148 | **550.857 | 213.837 | 614.475 | 368.112 | 778.450 | 376.288 |
| 대만 기권(^TWII) | | | 183.530 | 70.931 | 197.271 | 68.478 | 179.187 | 59.845 | **157.723 | 69.263 |
| 비트코인 암호화폐(BTC-USD) | | | 536.844 | 363.039 | **427.415 | 327.390 | 666.699 | 817.629 | 683.818 | 889.893 |
| Oil price(CL=F) | | | 3.894 | 2.953 | **2.794 | 2.216 | 3.594 | 3.203 | 3.180 | 2.238 |
| 이더리움 암호화폐(ETH-USD) | | | 50.980 | 44.595 | 36.175 | 26.770 | 34.514 | 27.134 | **50.385 | 39.829 |
| Gold price(GC=F) | | | 26.200 | 16.438 | **25.728 | 17.718 | 28.299 | 18.431 | 33.724 | 16.270 |

# Comparison results

- Mean Absolute Percentage Error (Normalized to each sequence)

| Data | Proposed | Standard Deviation | RNN | Standard Deviation | LSTM | Standard Deviation | GRU | Standard Deviation | Enc-Dec LSTM | Standard Deviation |
|---|---|---|---|---|---|---|---|---|---|---|
| 네덜란드 AEX(^AEX) | **0.01938 | 0.00575 | 0.02149 | 0.01151 | **0.01938 | 0.00575 | 0.02651 | 0.01254 | 0.02022 | 0.00925 |
| 인도 선섹스(^BSESN) | 0.02700 | 0.01201 | 0.01874 | 0.00637 | 0.02700 | 0.01201 | 0.02263 | 0.00982 | **0.01509 | 0.00650 |
| 브라질 보베스파(^BVSP) | 0.02444 | 0.01348 | **0.02367 | 0.00858 | 0.02444 | 0.01348 | 0.03200 | 0.01248 | 0.03465 | 0.01565 |
| 다우존스(^DJI) | 0.01926 | 0.00540 | 0.01884 | 0.00642 | 0.01926 | 0.00540 | **0.01879 | 0.00609 | 0.02153 | 0.01073 |
| 프랑스 CAC(^FCHI) | 0.02491 | 0.01165 | 0.02920 | 0.01604 | 0.02491 | 0.01165 | **0.01842 | 0.00936 | 0.02364 | 0.01140 |
| 독일 DAX(^GDAXI) | **0.02219 | 0.00922 | 0.02807 | 0.01809 | **0.02219 | 0.00922 | 0.02619 | 0.01290 | 0.02743 | 0.01374 |
| S&P 500(^GSPC) | 0.01704 | 0.00705 | 0.01934 | 0.01087 | 0.01704 | 0.00705 | **0.01425 | 0.00514 | 0.01949 | 0.01068 |
| 홍콩 항생(^HSI) | **0.01907 | 0.00639 | 0.02536 | 0.01034 | **0.01907 | 0.00639 | 0.02369 | 0.01168 | 0.02286 | 0.00739 |
| 스페인 IBEX(^IBEX) | **0.02437 | 0.01341 | 0.02469 | 0.01909 | **0.02437 | 0.01341 | 0.02631 | 0.01815 | 0.02631 | 0.01407 |
| NASDAQ(^IXIC) | 0.02108 | 0.00644 | **0.01863 | 0.00593 | 0.02108 | 0.00644 | 0.02229 | 0.00838 | 0.02689 | 0.01003 |
| KOSDAQ(^KQ11) | 0.03586 | 0.02034 | 0.03983 | 0.01357 | 0.03586 | 0.02034 | 0.03414 | 0.01655 | **0.03399 | 0.01325 |
| KOSPI(^KS11) | 0.01907 | 0.00631 | 0.01690 | 0.00552 | 0.01907 | 0.00631 | **0.01553 | 0.00614 | 0.01715 | 0.00803 |
| 일본 니케이(^N225) | **0.02795 | 0.01461 | 0.03159 | 0.02126 | **0.02795 | 0.01461 | 0.03230 | 0.02505 | 0.04045 | 0.02692 |
| 대만 기권(^TWII) | 0.01824 | 0.00751 | 0.01696 | 0.00828 | 0.01824 | 0.00751 | 0.01643 | 0.00649 | **0.01453 | 0.00793 |
| 비트코인 암호화폐(BTC-USD) | **0.05769 | 0.02862 | 0.07405 | 0.03593 | **0.05769 | 0.02862 | 0.08609 | 0.07321 | 0.07933 | 0.06390 |
| Oil price(CL=F) | 0.04872 | 0.05775 | 0.07050 | 0.08610 | 0.04872 | 0.05775 | 0.06203 | 0.07696 | **0.04769 | 0.03948 |
| 이더리움 암호화폐(ETH-USD) | **0.10787 | 0.09124 | 0.14305 | 0.09475 | **0.10787 | 0.09124 | 0.11357 | 0.07691 | 0.14004 | 0.08726 |
| Gold price(GC=F) | **0.01484 | 0.01028 | 0.01556 | 0.00919 | **0.01484 | 0.01028 | 0.01643 | 0.01052 | 0.02061 | 0.00972 |

# Comparison results

- Mean Absolute Error (Normalized to each sequence)

| Data | Proposed | Standard Deviation | LSTM | Standard deviation | Attention-LSTM | Standard deviation |
|---|---|---|---|---|---|---|
| KOSPI(^KS11) | | | 39.714 | 13.813 | 17.250 | 8.260 |
| KOSDAQ(^KQ11) | | | 25.220 | 14.498 | 7.857 | 4.167 |
| NASDAQ(^IXIC) | | | 122.264 | 41.803 | 58.532 | 38.878 |
| S&P 500(^GSPC) | | | 40.281 | 20.761 | 19.206 | 12.596 |
| 다우존스(^DJI) | | | 386.981 | 130.981 | 178.295 | 123.787 |
| 홍콩 항생(^HSI) | | | 464.189 | 119.809 | 274.359 | 140.845 |
| 일본 니케이(^N225) | | | 482.213 | 198.073 | 201.528 | 77.740 |
| 독일 DAX(^GDAXI) | | | 236.222 | 97.034 | 124.023 | 53.905 |
| 영국 | | | | | 62.119 | 30.127 |
| 프랑스 CAC(^FCHI) | | | 114.632 | 47.652 | 48.697 | 23.605 |
| 대만 기권(^TWII) | | | 172.253 | 62.575 | 70.467 | 26.273 |
| Gold price(GC=F) | | | 20.112 | 14.340 | 0.435 | 0.276 |
| Oil price(CL=F) | | | 1.990 | 0.913 | 0.719 | 0.419 |
| 중국 CSI | | | | | 41.503 | 21.909 |
| 상해 종합 | | | | | 34.387 | 22.425 |
| 배트남 하노이 | | | | | 2.003 | 0.805 |

# Comparison results

- Root Mean Squared Error (Normalized to each sequence)

| Data | Proposed | Standard Deviation | LSTM | Standard deviation | Attention-LSTM | Standard deviation |
|---|---|---|---|---|---|---|
| KOSPI(^KS11) | | | 44.939 | 14.383 | 21.683 | 10.130 |
| KOSDAQ(^KQ11) | | | 29.395 | 16.572 | 10.026 | 5.095 |
| NASDAQ(^IXIC) | | | 144.600 | 50.219 | 76.243 | 53.801 |
| S&P 500(^GSPC) | | | 47.002 | 25.976 | 25.206 | 18.582 |
| 다우존스(^DJI) | | | 447.909 | 167.888 | 232.836 | 174.092 |
| 홍콩 항생(^HSI) | | | 540.112 | 120.722 | 340.568 | 156.537 |
| 일본 니케이(^N225) | | | 550.857 | 213.837 | 261.827 | 92.105 |
| 독일 DAX(^GDAXI) | | | 274.045 | 103.857 | 156.229 | 67.232 |
| 영국 | | | | | 78.305 | 34.973 |
| 프랑스 CAC(^FCHI) | | | 132.486 | 56.154 | 61.816 | 28.576 |
| 대만 기권(^TWII) | | | 197.271 | 68.478 | 90.073 | 33.408 |
| Gold price(GC=F) | | | 25.728 | 17.718 | 0.618 | 0.398 |
| Oil price(CL=F) | | | 2.794 | 2.216 | 0.926 | 0.480 |
| 중국 CSI | | | | | 54.030 | 28.348 |
| 상해 종합 | | | | | 44.479 | 28.587 |
| 배트남 하노이 | | | | | 2.626 | 1.059 |

# Comparison results

- Mean Absolute Percentage Error (Normalized to each sequence)

| Data | Proposed | Standard Deviation | LSTM | Standard deviation | Attention-LSTM | Standard deviation |
|---|---|---|---|---|---|---|
| KOSPI(^KS11) | | | 0.01907 | 0.00631 | 0.00851 | 0.00455 |
| KOSDAQ(^KQ11) | | | 0.03586 | 0.02034 | 0.01224 | 0.00758 |
| NASDAQ(^IXIC) | | | 0.02108 | 0.00644 | 0.00991 | 0.00531 |
| S&P 500(^GSPC) | | | 0.01704 | 0.00705 | 0.00842 | 0.00512 |
| 다우존스(^DJI) | | | 0.01926 | 0.00540 | 0.00882 | 0.00569 |
| 홍콩 항생(^HSI) | | | 0.01907 | 0.00639 | 0.01123 | 0.00636 |
| 일본 니케이(^N225) | | | 0.02795 | 0.01461 | 0.01128 | 0.00567 |
| 독일 DAX(^GDAXI) | | | 0.02219 | 0.00922 | 0.01218 | 0.00704 |
| 영국 | | | | | 0.00947 | 0.00505 |
| 프랑스 CAC(^FCHI) | | | 0.02491 | 0.01165 | 0.01077 | 0.00623 |
| 대만 기권(^TWII) | | | 0.01824 | 0.00751 | 0.00747 | 0.00324 |
| Gold price(GC=F) | | | **0.01484 | 0.01028 | 0.01680 | 0.00747 |
| Oil price(CL=F) | | | 0.04872 | 0.05775 | 0.01091 | 0.00733 |
| 중국 CSI | | | | | 0.01241 | 0.00691 |
| 상해 종합 | | | | | 0.01166 | 0.00666 |
| 배트남 하노이 | | | | | 0.01047 | 0.00368 |

# Comparison results

- Summary

  - Attention LSTM이 대부분의 경우에서 좋은  성능을 보임

  - 상당수의 Error 값이 2배 이상 적음

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# Appendix

# Appendix

- Jarque-bera test

- 왜도와 첨도가 정규분포와 일치하는지 판단하는 적합도 검정

- ADF test

- 시계열 데이터가 정상성(stationary)을 만족하는지에 대한 검정

- LM-ARCH 검정

- ARCH, GARCH와 같은 모형을 적용할 수 있는지에 대한 검정.