Transformer time series prediction

Tae-Won Lee,
leetee95@gmail.com
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Introduction

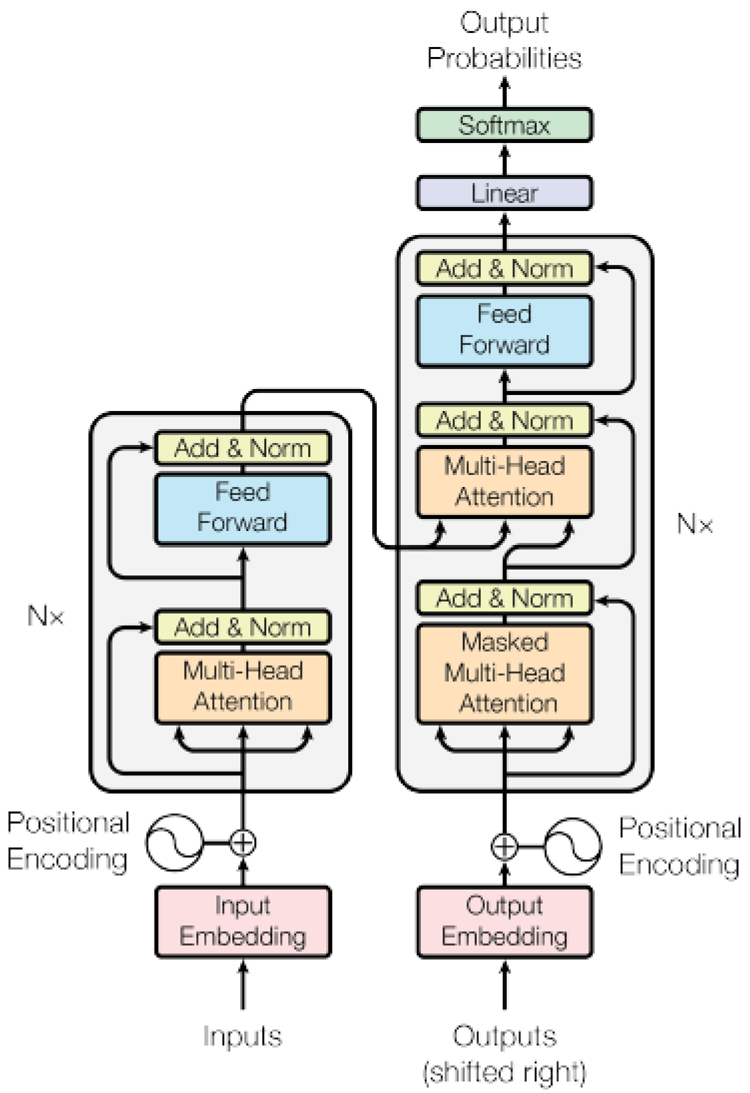
- Attention LSTM 구조에서 LSTM을 삭제시킨 구조.

- LSTM구조의 삭제와 Positional Encoding을 활용해 시계열의 병렬적인 계산 가능.

- 충분히 긴 sequence의 예측에서 높은 효율성을 보임

Related works

- Transformer structure
  - Encoder
    - Multi-Head Attention + Feed Forward
  - Decoder
    - Multi-Head Attention + Feed Forward + Masked Multi-Head Attention
  - Positional Encoding



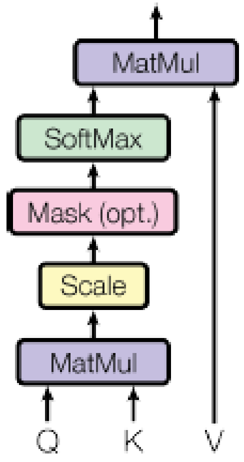
Related works

- Multi-Head Attention structure

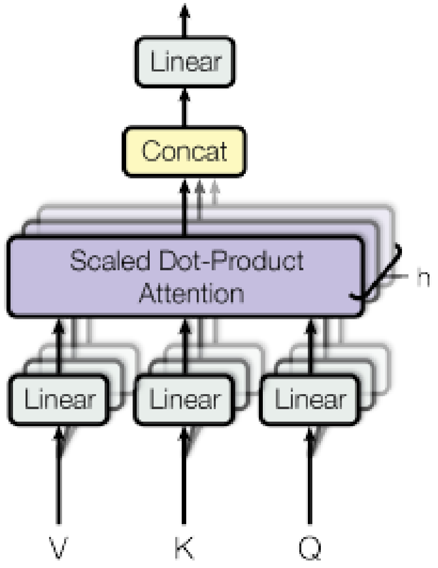
$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, \ldots, \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Scaled Dot-Product Attention



Multi-Head Attention

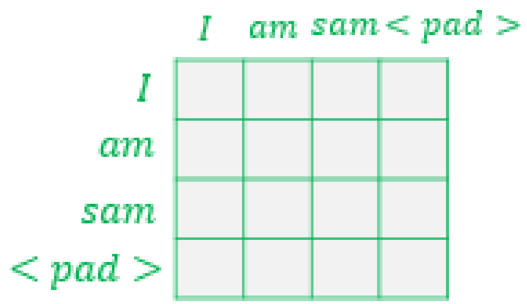


Related works

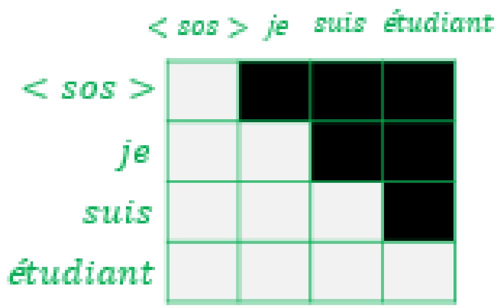
- Masked Multi-Head Attention structure

  - Decoder단계에서 Look ahead가 발생

  - 자기 자신과 이전 정보만을 참고



Attention Score Matrix



Attention Score Matrix

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

- 최근 동향

학회 명		IF	논문 명	발간 년도	인용 수	내용
IEEE ACCESS	SCIE	3.7	A Prediction Approach for Stock Market Volatility Based on Time Series Data	2019	48	전통적인 통계적 방식을 이용한 시계열 예측의 개요
International Conference on Big Data		0.75	Applied attention-based LSTM neural networks in stock prediction	2018	22	Attention mechanism을 이용한 주식 가격 예측
Expert Systems With Applications	SCIE	8.67	CNNpred: CNN-base d stock market prediction using a diverse set of variables Related work	2019	79	Cnn을 이용하여 Automatic feature 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 LSTM-based Hong Kong stock price movement prediction	2019	19	Attention 구조를 이용한 주식가격 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 transform, 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 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
  - MAE($e^{predicted\ value}, e^{true\ value}$)
  - RMSE($e^{predicted\ value}, e^{true\ value}$)
  - 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

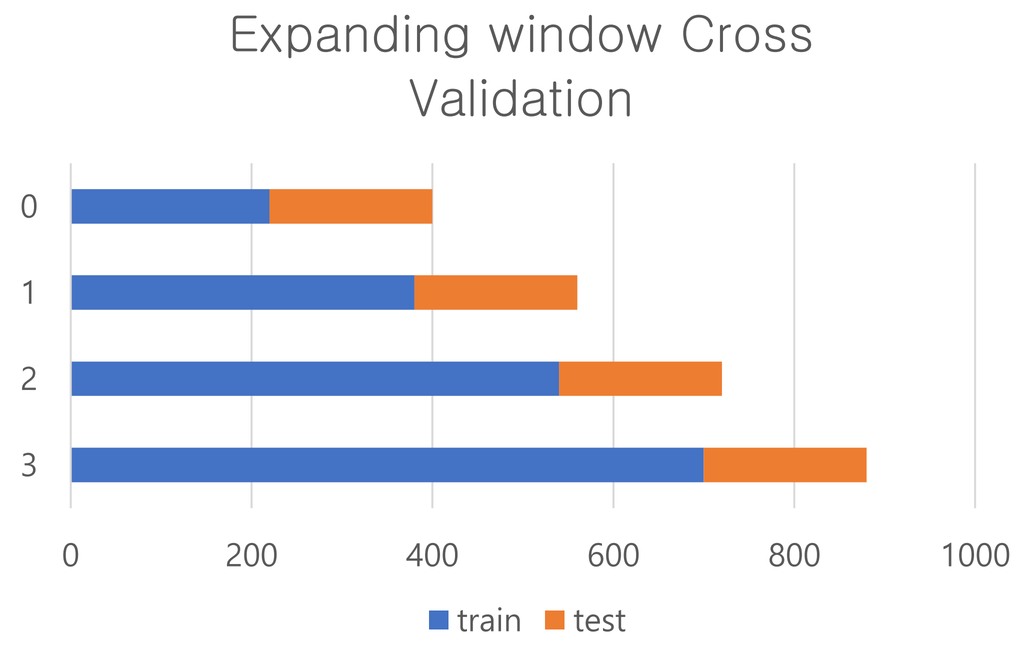
- To determine the detailed performance of a model
  - Add another model evaluation metric.
    - Mean Absolute Percentage Error (MAPE) = $\frac{\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right|}{n}\cdot 100(\%)$
      - MAPE is undefined for data points where the value is zero.
      - MAPE is biased towards prediction that are systemically less than the actual values themselves

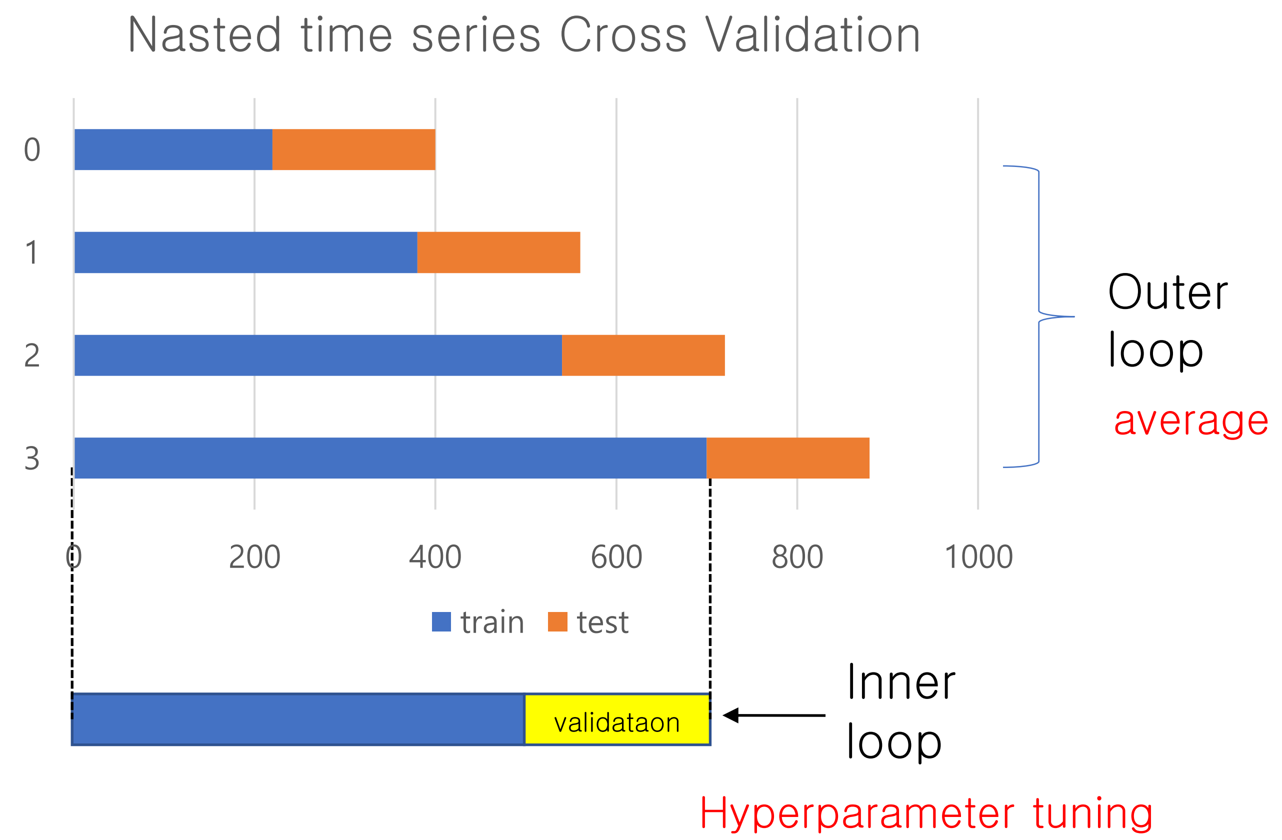
$$y = 20, \hat{y} = 10, n = 1 \ \rightarrow MAPE = 50\%$$
$$y = 10, \hat{y} = 20, n = 1 \ \rightarrow MAPE = 100\%$$

  - Compare three metrics.
    - MAE
    - RMSE
    - MAPE

Experimental setting

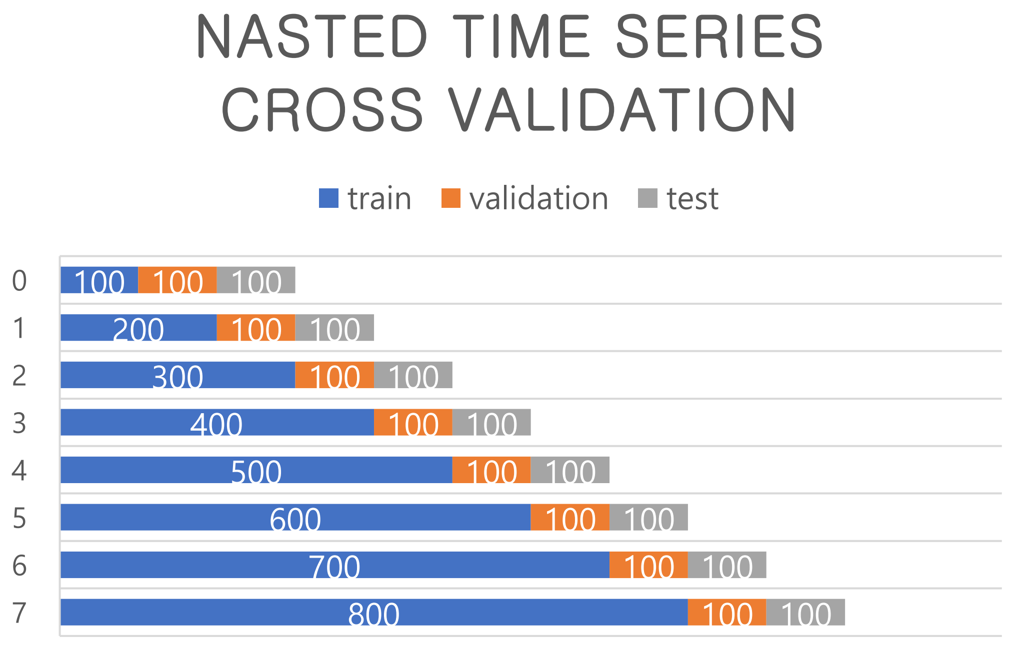
- Stock dataset split in timeseries data





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	LSTM [11]	Standard Deviation	Enc-Dec LSTM [12]	Standard Deviation	Attention-LSTM [13]	Standard Deviation	Transformer	Standard Deviation
KOSPI(KS11)			52.269	16.096	45.915	21.731	17.250	8.260	1.190	1.724
KOSDAQ(KQ11)			20.508	11.049	18.530	10.324	7.857	4.167	0.489	0.782
NASDAQ(IXIC)			140.401	65.606	157.117	69.279	58.532	38.878	1.487	1.338
S&P 500(US500)			41.112	11.981	42.704	21.420	19.206	12.596	0.537	0.699
다우존스(DJI)			356.113	133.257	437.524	264.019	178.295	123.787	8.017	14.514
홍콩 항생(HK50)			709.597	320.772	546.580	120.305	274.359	140.845	9.132	8.818
일본 니케이(JP225)			626.806	227.996	655.157	243.966	201.528	77.740	21.181	45.055
독일 DAX(DE30)			302.292	180.307	284.468	113.072	124.023	53.905	4.710	7.007
영국(UK100)			153.512	76.844	137.754	61.359	62.119	30.127	4.221	7.693
프랑스 CAC(FCHI)			129.893	41.228	122.388	62.802	48.697	23.605	1.788	2.340
대만 기권(TWII)			158.075	67.362	134.362	54.172	70.467	26.273	3.661	5.811
Gold price(GC)			0.930	0.379	0.741	0.271	0.435	0.276	0.015	0.010
Oil price(CL)			1.582	0.671	1.083	0.350	0.719	0.419	0.020	0.020
상해 종합(SSEC)			81.627	99.271	102.138	105.932	34.387	22.425	1.338	1.174
배트남 하노이(HNX30)			6.446	4.547	4.998	3.410	2.003	0.805	0.103	0.089

Comparison results

- Root Mean Squared Error (Normalized to each sequence)

Data	Proposed	Standard Deviation	LSTM [11]	Standard Deviation	Enc-Dec LSTM [12]	Standard Deviation	Attention-LSTM [13]	Standard Deviation	Transformer	Standard Deviation
KOSPI(KS11)			58.669	17.005	53.453	24.670	21.683	10.130	1.586	2.329
KOSDAQ(KQ11)			23.446	12.091	21.173	11.706	10.026	5.095	0.634	0.998
NASDAQ(IXIC)			159.799	73.093	177.779	77.271	76.243	53.801	1.874	1.613
S&P 500(US500)			47.623	15.881	49.705	25.414	25.206	18.582	0.683	0.840
다우존스(DJI)			421.385	170.491	517.107	346.696	232.836	174.092	9.587	16.815
홍콩 항생(HK50)			802.987	353.642	648.929	152.322	340.568	156.537	11.944	11.473
일본 니케이(JP225)			721.720	263.764	759.353	287.823	261.827	92.105	26.243	53.999
독일 DAX(DE30)			354.197	221.421	329.801	125.248	156.229	67.232	6.354	9.133
영국(UK100)			183.228	86.025	166.142	74.387	78.305	34.973	5.274	9.135
프랑스 CAC(FCHI)			148.157	47.911	142.074	75.492	61.816	28.576	2.235	2.749
대만 기권(TWII)			191.475	82.745	158.479	61.736	90.073	33.408	4.580	6.844
Gold price(GC)			1.230	0.527	1.017	0.401	0.618	0.398	0.022	0.013
Oil price(CL)			1.835	0.627	1.341	0.411	0.926	0.480	0.026	0.022
상해 종합(SSEC)			96.571	111.584	119.350	117.891	44.479	28.587	1.747	1.487
배트남 하노이(HNX30)			7.304	4.939	5.717	3.623	2.626	1.059	0.142	0.122

Comparison results

- Mean Absolute Percentage Error (Normalized to each sequence)

Data	Proposed	Standard Deviation	LSTM [11]	Standard Deviation	Enc-Dec LSTM [12]	Standard Deviation	Attention-LSTM [13]	Standard Deviation	Transformer	Standard Deviation
KOSPI(KS11)			0.02470	0.00799	0.02166	0.01108	0.00851	0.00455	0.00058	0.00086
KOSDAQ(KQ11)			0.03224	0.01956	0.02807	0.01626	0.01224	0.00758	0.00086	0.00147
NASDAQ(IXIC)			0.02362	0.00754	0.02686	0.01003	0.00991	0.00531	0.00031	0.00038
S&P 500(US500)			0.01845	0.00677	0.01946	0.01065	0.00842	0.00512	0.00029	0.00044
다우존스(DJI)			0.01765	0.00648	0.02150	0.01075	0.00882	0.00569	0.00049	0.00098
홍콩 항생(HK50)			0.02907	0.01435	0.02214	0.00578	0.01123	0.00636	0.00038	0.00039
일본 니케이(JP225)			0.03463	0.01485	0.03617	0.01575	0.01128	0.00567	0.00139	0.00308
독일 DAX(DE30)			0.02918	0.01838	0.02750	0.01365	0.01218	0.00704	0.00053	0.00088
영국(UK100)			0.02321	0.01238	0.02096	0.01073	0.00947	0.00505	0.00064	0.00117
프랑스 CAC(FCHI)			0.02831	0.01145	0.02641	0.01441	0.01077	0.00623	0.00042	0.00061
대만 기권(TWII)			0.01680	0.00828	0.01440	0.00699	0.00747	0.00324	0.00043	0.00072
Gold price(GC)			0.03601	0.01071	0.03059	0.01329	0.01680	0.00747	0.00085	0.00106
Oil price(CL)			0.02382	0.01169	0.01616	0.00615	0.01091	0.00733	0.00030	0.00031
상해 종합(SSEC)			0.02525	0.02362	0.03207	0.02409	0.01166	0.00666	0.00049	0.00050
배트남 하노이(HNX30)			0.03150	0.01939	0.02549	0.01488	0.01047	0.00368	0.00057	0.00059

Comparison results

- Execution time

Data	Proposed	LSTM [11]	Enc-Dec LSTM [12]	Attention-LSTM [13]	Transformer
KOSPI(KS11)		377.839	368.567	486.881	421.637
KOSDAQ(KQ11)		448.653	497.858	487.970	536.399
NASDAQ(IXIC)		472.790	467.439	515.746	534.615
S&P 500(US500)		450.805	466.514	487.306	535.056
다우존스(DJI)		455.009	468.064	540.474	534.305
홍콩 항생(HK50)		431.069	447.140	491.001	505.243
일본 니케이(JP225)		431.893	474.211	461.090	505.808
독일 DAX(DE30)		455.151	468.867	517.094	534.126
영국(UK100)		444.334	454.792	473.904	518.930
프랑스 CAC(FCHI)		455.020	467.980	488.779	533.952
대만 기권(TWII)		449.197	490.981	482.663	526.779
Gold price(GC)		454.917	468.068	489.279	533.721
Oil price(CL)		455.306	467.408	487.658	533.972
상해 종합(SSEC)		455.527	467.553	487.021	533.986
배트남 하노이(HNX30)		329.476	306.398	319.439	349.763

Comparison results

- Issue
  - Decoder 단계에서 look ahead prediction이 발생하여 과도하게 좋은 예측결과 발생

- 해결방안
  1) Decoder를 제거하고 Encoder에서 linear layer를 거쳐 output을 산출하는 방법

  2) Decoder를 제거하지 않고 Mask 단계에서 해당 예측시점 데이터까지 Masking 하는 방법

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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.

Appendix

- 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)

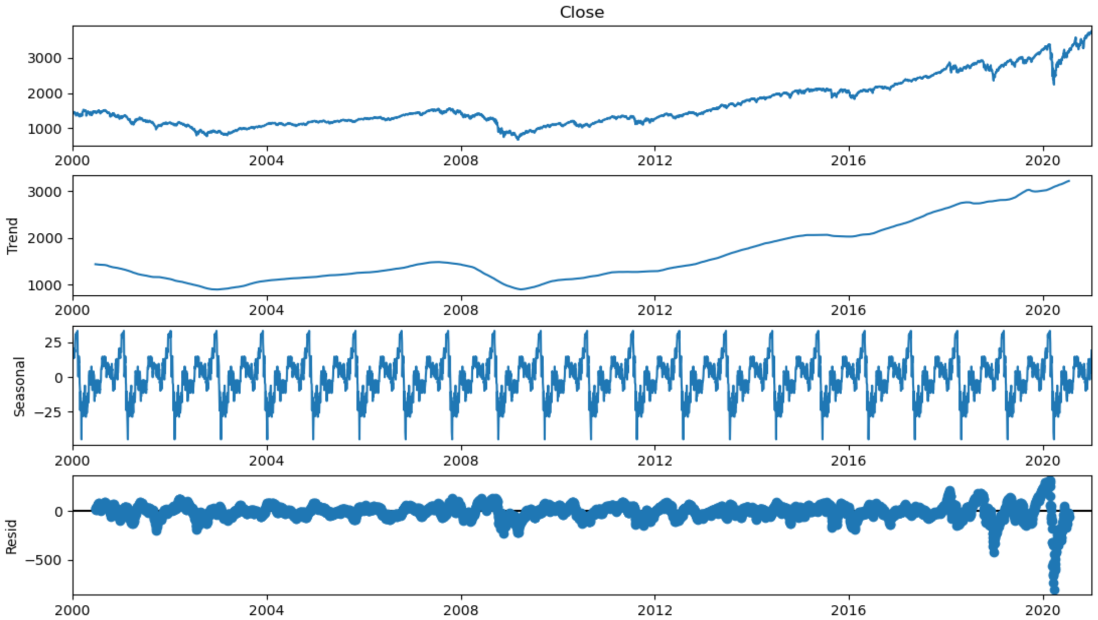
 - normalization applied to entire sequence

 “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

Appendix

- 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.

Appendix

- 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

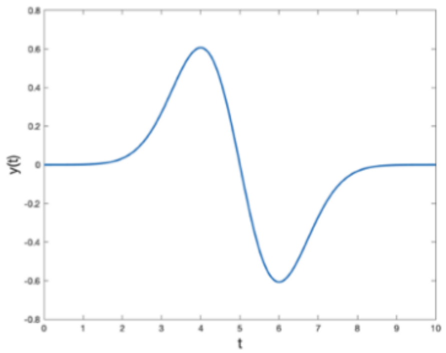
Appendix

- 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

Appendix

- 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