

Stock Index Prediction with Machine Learning and Deep Learning Models

Hong Thanh Hoai, Mai Hoang Lan, Nguyen Thi Hong Phuc

Vingroup Big Data Institute

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Problem Overview

Why Predict Stock?

- Maximize profits
- Predict the economy
- Implement suitable economic policies

Challenges

- Stochastic nature
- Multiple factors

Project Objectives

What are the Goals?

- Build a working ARIMA (Autoregressive Moving Average) model
- Build a working LSTM model
- Build a working CNN model
- Build a working feature fusion LSTM - CNN model
- Outputs: predicted daily closing for Dow Jones Industrial Average (DJIA)

$$DJIA = \frac{\sum \text{stock price}}{d}; \text{ Dow divisor: } d \approx 0.152$$

Data Overview - Dow Jones 2009-2017

	Date	Open	High	Low	Close	Adj Close	Volume
0	2009-01-02	8772.250000	9065.280273	8760.780273	9034.690430	9034.690430	213700000
1	2009-01-05	9027.129883	9034.370117	8892.360352	8952.889648	8952.889648	233760000
2	2009-01-06	8954.570313	9088.059570	8940.950195	9015.099609	9015.099609	215410000
3	2009-01-07	8996.940430	8996.940430	8719.919922	8769.700195	8769.700195	266710000
4	2009-01-08	8769.940430	8770.019531	8651.190430	8742.459961	8742.459961	226620000

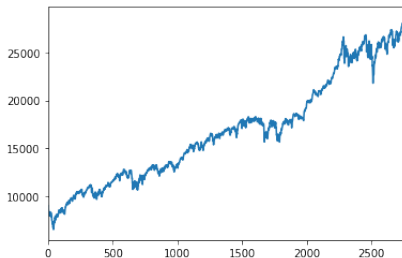
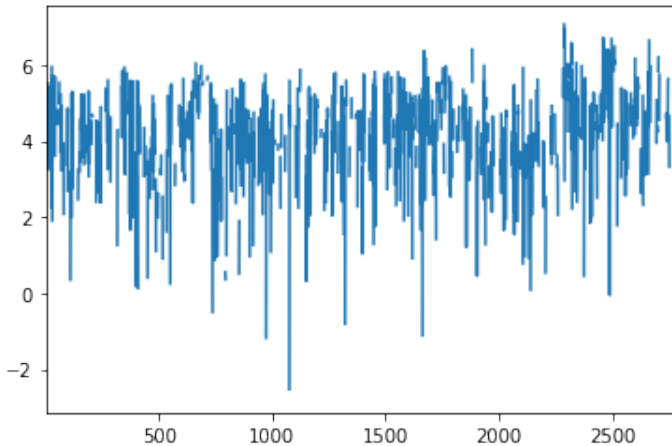


Figure: 2767 days in total. (Train set: 1660 — Test set: 553)

Data Overview - Dow Jones 2009-2017



ARIMA Model Results

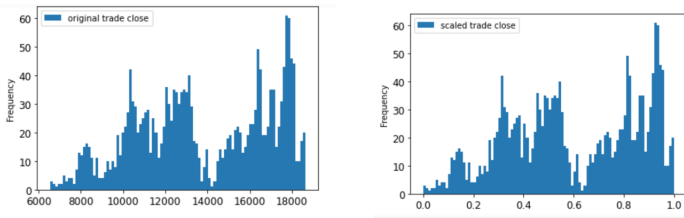
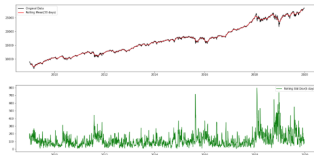


Figure: Original Trade Close and Scaled Trade Close

ARIMA Model Results

Dickey-Fuller test results

```
Test Statistic      0.220418
p-value             0.973384
# of lags           26.000000
# of obs            2740.000000
dtype: float64
Critical value at 1%: -3.43274
Critical value at 5%: -2.86260
Critical value at 10%: -2.56733
```



Dickey-Fuller test results

```
Test Statistic      -1.127456e+01
p-value             1.507773e-20
# of lags           2.500000e+01
# of obs            2.740000e+03
dtype: float64
Critical value at 1%: -3.43274
Critical value at 5%: -2.86260
Critical value at 10%: -2.56733
```

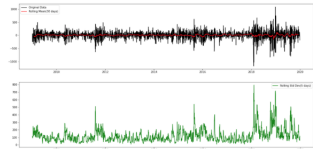


Figure: Test for Data Stationarity

ARIMA Model Results

Hyper-parameters estimation:

- Differencing (d): make time series stationary, avoiding over-differenced series.
- Auto-Regression AR (p): Investigating Partial Auto-correlation (PACF) for defining p
- Moving Average MA (q): Investigating Auto-correlation (ACF) for estimating q

ARIMA Model Results

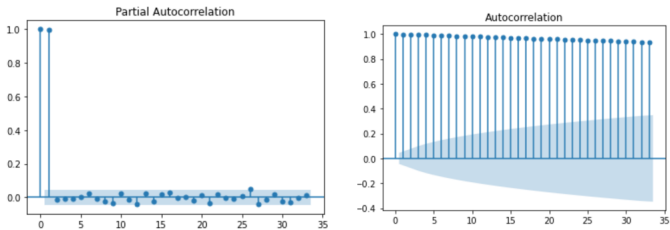


Figure: PACF and ACF plot

ARIMA Model Results

```
=====
                        SARIMAX Results
=====
Dep. Variable:          Close      No. Observations:      1936
Model:                 ARIMA(1, 1, 1)  Log Likelihood      6068.774
Date:                 Sun, 27 Dec 2020  AIC                -12131.548
Time:                 02:43:23         BIC                -12114.844
Sample:              0               HQIC               -12125.404
                        - 1936
Covariance Type:      opg
=====
                        coef      std err      z      P>|z|      [0.025      0.975]
-----
ar.L1                -0.5159      0.254      -2.033      0.042      -1.013      -0.018
ma.L1                 0.4718      0.262      1.797      0.072      -0.043      0.986
sigma2                0.0001     2.5e-06     44.166      0.000      0.000      0.000
=====
Ljung-Box (L1) (Q):                0.01  Jarque-Bera (JB):                409.21
Prob(Q):                          0.94  Prob(JB):                  0.00
Heteroskedasticity (H):            1.73  Skew:                   -0.32
Prob(H) (two-sided):              0.00  Kurtosis:                5.16
=====
```

Figure: Results for ARIMA Model(1,1,1)

ARIMA Model Results

	timestamp	h	prediction	actual
1	8/10/15	t+1	17370.500507	17615.16992
2	8/11/15	t+1	17685.151502	17402.83984
3	8/12/15	t+1	17361.905542	17402.50977
4	8/13/15	t+1	17412.633924	17408.25000
5	8/14/15	t+1	17401.151941	17477.40039

Figure: Predictions from ARIMA

ARIMA Model Results

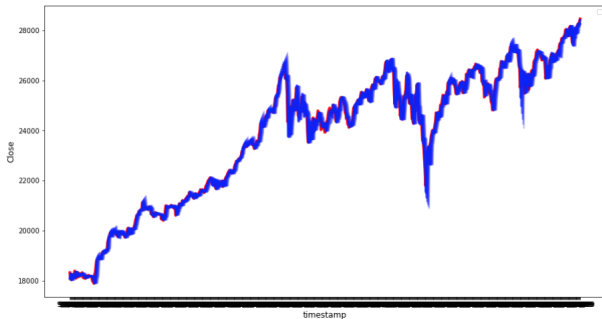


Figure: Plot of Actual and Predicted Values

RMSE=274.9319, MAE=182.287

LSTM Model Results

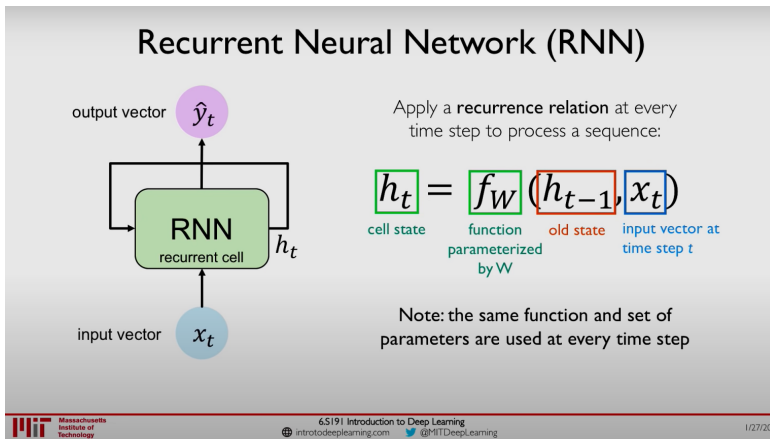


Figure: Simple RNN diagram (Courtesy of MIT) [4]

LSTM Model Results

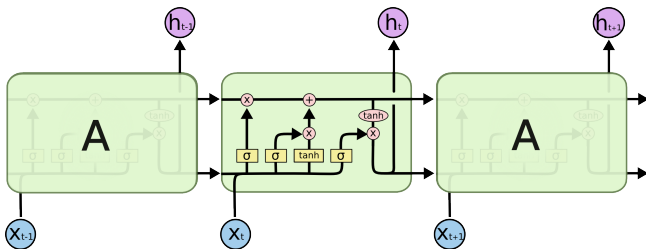


Figure: LSTM architecture [3]

Input: $\log \frac{Close_t}{Close_{t-1}}, \log \frac{Close_{t+1}}{Close_t}, \log \frac{Close_{t+2}}{Close_{t+1}}, \log \frac{Close_{t+3}}{Close_{t+2}} \dots$

Output: $\log \frac{Close_{t+33}}{Close_{t+28}}$

LSTM Model Results (Training)

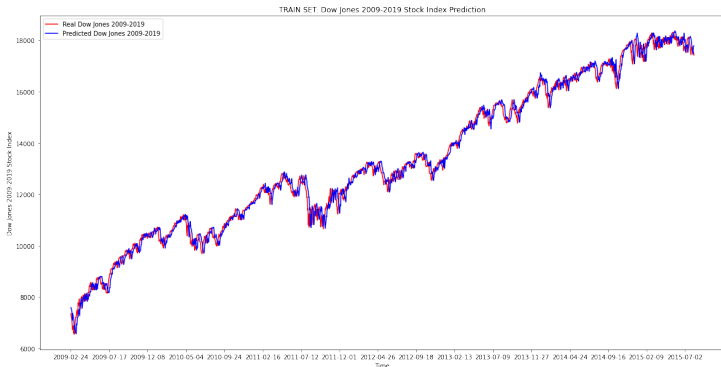


Figure: LSTM Model on Training Set

RMSE = 263.2288, MAE = 208.7557

LSTM Model Results (Testing)

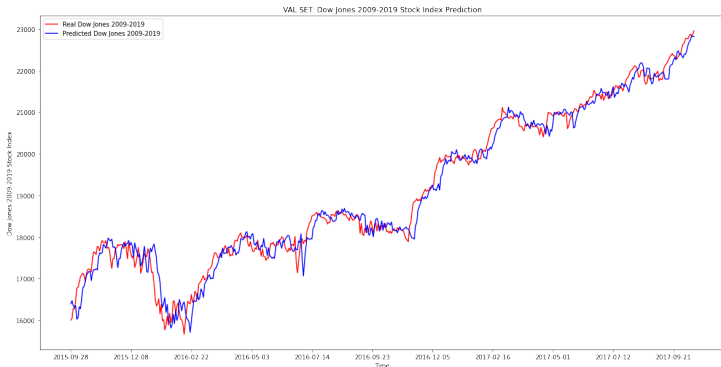


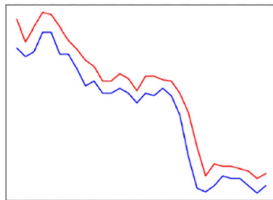
Figure: LSTM Model on Test Set

RMSE = 296.7456, MAE = 228.3258

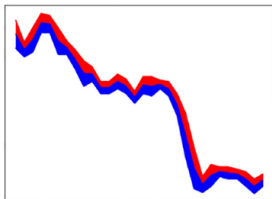
CNN Model Results



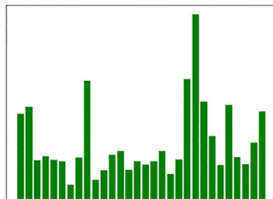
(a)



(b)



(c)



(d)

CNN Model Results (Training)

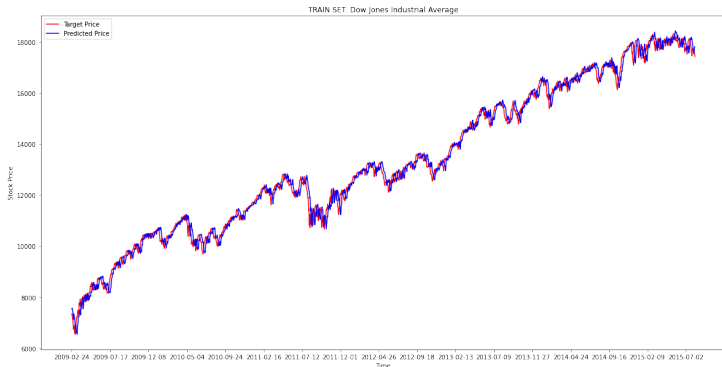


Figure: CNN Model on Training Set

RMSE = 250.6945, MAE = 191.6990

CNN Model Results (Testing)

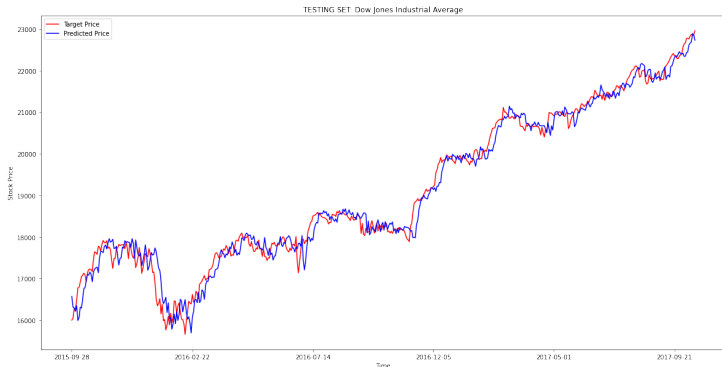
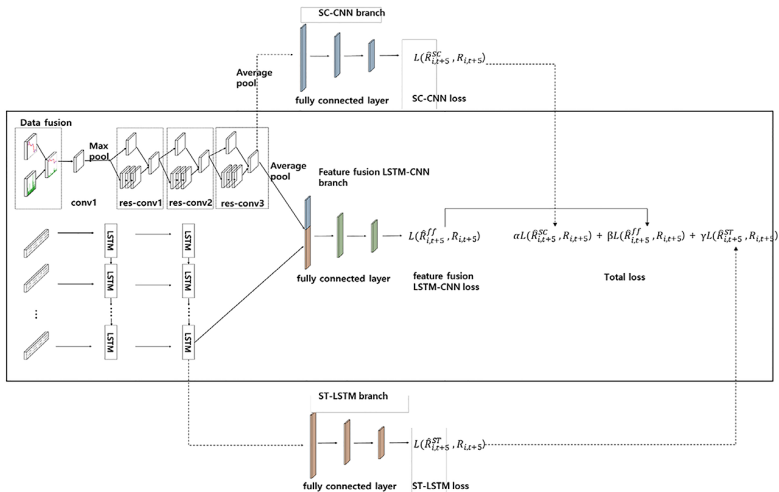


Figure: CNN Model on Test Set

RMSE = 270.6161, MAE = 201.3691

LSTM-CNN Model Results



LSTM-CNN Model Results (Training)



Figure: LSTM-CNN Model on Training Set

RMSE = 251.2169, MAE = 191.4447

LSTM-CNN Model Results (Testing)

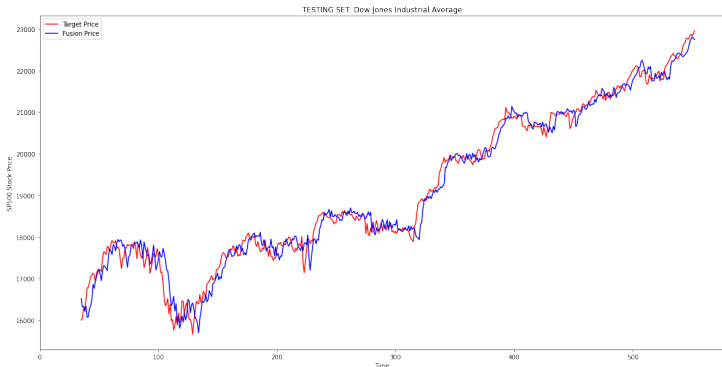


Figure: LSTM-CNN Model on Test Set

RMSE = 267.5648, MAE = 198.2916

Model Comparison

Table 1: Result on Dow Jones Industrial Average (DJI) (Test Set)

	RMSE	MAE
ARIMA	274.9319	182.2872
LSTM	296.7456	228.3258
CNN	270.6161	201.3691
LSTM-CNN	269.0664	198.8619





Figure: Model Comparison

Future Work

- Implement sentiment analysis to extract relevant stock news.
- Implement Generative Adversarial Network (GAN) with LSTM.
- Use Deep Reinforcement Learning (DRL) for deciding GAN's hyper-parameters.

Reference

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