Foreign Exchange Rates prediction with LSTM

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1 Abstract

Foreign Exchange (abbreviation *Forex* or simply *FX*) Market is the decentralized market for currency investment. Forex market is the second most important market, after stock market. Supply and demand in the market determine Forex rate, in which a pair of currency can be exchanged. Forex Rates has been studied in econometrics as a financial timeseries. The purpose of studying Forex rates is to explain the market behaviour or forecast future prices.

In our project, we use statistical models and deep learning model to predict the future rates of one step ahead. Our goal is to compare the effectiveness of LSTM and statistical models (ARIMA and VAR) as timeseries models, in both accuracy and performance.

2 Problem Description

2.1 Forex rates

Foreign Exchange rates (short Forex rates) are decided solely by support and demand of Forex market. Each rate represents the price to buy or sell a pair of currency (e.g. EURUSD) at the moment. The price to buy is called Bid price; the price to sell is called Ask price. The difference between Bid price and Ask price is called Spread. In this project we consider only the Bid price. However, if both Bid and Ask (and therefore Spread) were available, our analysis would be more precise.

Forex brokers update rates according to the market within milliseconds by standardized FIX (Financial Information eXchange) protocol. The time interval between FIX market update messages are not uniform; it may varies from a millisecond to few seconds. Therefore, the timeseries is of continuous time step. In order to simplify our analysis, we convert it to a data form that has discrete, uniform time step, while still keep important information. One possible way to do so is to format the rates into OHLC format. This approach is widely used in financial technical analysis. We partition the timeseries into intervals of uniform time length t. For each interval, we keep only 4 rate: the first (*open*), the last (*close*), the maximum (*high*), the minimum (*low*). Since the time intervals are uniform among dataset, we have the desired discrete, uniform time step for analysis.

(a) Original rates and OHLC form   (b) Candlestick

Figure 1: Illustration of OHLC timeseries formatting.

2.2 Prediction

In this project, we concern about the prediction of future Open, High, Low, Close prices. Other features, either originally exists (volume) or later added (mean, median, momentum), are only considered as supporting features. These features are only used for prediction of OHLC features.

The problem we are trying to solve in this project is declared as follow: given history data in OHLC form of Forex rates, namely $x_0, x_1, \ldots, x_k$ where $x_i = (x_i^O, x_i^H, x_i^L, x_i^C)$, predict future rate of *one* step ahead, x_{k+1}.

2.3 Dataset

Acquiring real-time data is expensive, due to the fact that most FIX data providers requires subscription contract. However, Janus [2] collected an EURUSD rate dataset. The dataset consists of OHLC of BID price (no ASK price) of EURUSD rates from 2010 to 2016, thus contains 245444 values. Time interval for OHLC value is uniformly set to 15 minutes. Janus also published a smaller sample subset of the dataset, which contains only 14880 values. We would use the sample dataset later for ARIMA parameter search to reduce computational effort.

We separate 245444 records into 3 sets: train set, validation set, test set. In our default configuration, 80% of the dataset is trainset (19636 records), 10% is valid set (2454 records), 10% test set.

3 Model Selection and Evaluation

3.1 Akaike Information Criterion (AIC)

Akaike Information Criterion (AIC) is basically log-likelihood, but it penalizes a model by the number of parameters. AIC is widely used in statistical model selection, not only ARIMA and VAR, but also Hidden Markov Model and so on.

$$AIC = 2k - 2\ln(\hat{L})$$

in which k is the number of parameters and $\hat{L}$ is the likelihood. Since the log-likelihood is multiplied by -1, lower AIC means the model fits better to the data.

3.2 Root Mean Squared Error (RMSE)

Root Mean Squared Error is widely used to measure the difference between values predicted by a model and the actually observed values. Given y represents the actually observed values and $\hat{y}$ represents the values predicted, $RMSE$ is given by:

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \right)^{\frac{1}{2}}$$

Root Mean Squared Error shows difference between y and $\hat{y}$ regardless the difference is negative or positive. However, since it does not take the range of possible values into account, it would be difficult to intepret the $RMSE$ result without knowing the possible range of predicted and actual values.

3.3 Mean Absolute Percentage Error (MAPE)

In order to measure the difference between predicted values and actual values with regarding to the scale, we use Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

Compare to RMSE, MAPE is easier to interpret, for it is only a ratio without unit. Knowing the Max-Min range of the data beforehand is not necessary. The drawback could be the absolute value function, which is not continuous and thus make it difficult to take it as a loss function. However, we do not use it as a loss function here.

4 Statistical Models

4.1 Basic of Time series.

Let $\{x_t\}$ is a timeseries with $\mu = \mu(t)$ is its mean and $\sigma = \sigma(t)$ is its variance. **Autocovariance** of lag k is defined as $C_k = E[(x_t - \mu)(x_{t+k} - \mu)]$ and **autocorrelation** is defined as $\rho_k = \frac{C_k}{\sigma^2}$.

A time series $\{e_t\}$ is a *discrete white noises* if its elements e_i are independent, identically distributed, have mean equals to zero and no autocorrelation between any of its values. Formally, $\mu_{\{e_t\}} = \mu_{\{e_t\}}(t) = 0$, $Cor(e_i, e_j) \neq 0, \forall i \neq j$.

A time series $\{x_t\}$ is a *random walk* if it satisfies that $x_t = x_{t-1} + e_t$ where $\{e_t\}$ is a discrete white noise as described above.

The following models we consider are similar to linear regression to some extents. Their rationales is that we find a linear relation between the value at time t and certain *lags* before it . Detailed explanation of the models can be found at [5] and [3].

4.2 ARIMA(p,d,q)

4.2.1 Model description

ARIMA(p,d,q) consists of three models: $AR(p)$, $MA(q)$ and integrated series of order d.

A timeseries $\{x_t\}$ is a *Auto-Regression $AR(p)$* if it satisfies that

$$x_t = \alpha_1 x_{t-1} + \ldots + \alpha_{t-p} x_{t-p} + e_t$$

where $\{e_t\}$ is discrete white noises. So, *AR(p)* model looks back to find a linear relation with p previous values. Normally, we use Autocorrelation Plot (ACF) of log difference to find p, which is the highest lag in which we find a significant autocorrelation.

A timeseries $\{x_t\}$ is a *Moving Average $AR(p)$* if it satisfies that

$$x_t = \alpha_1 e_{t-1} + \ldots + \alpha_{t-p} e_{t-p} + e_t$$

where $\{e_t\}$ is discrete white noises. The coefficients α_i are estimated, for example with maximum likelihood, by a sample (in our case, train set) to Instead of looks back into values, *MA(q)* looks into *differences* between timesteps, assuming that the timeseries is a random walk (thus differences between timesteps are discrete white noises). To find parameter q, normally

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we look at the Partial Autocorrelation Plot (PACF) to find the lag in which autocorrelation start to decay.

In the next section, we consider another method for parameters selection that would give us the optimal parameter set (p,d,q) at once.

4.2.2 Parameters selection

Another method is that we try all possible combination of p, d and q to find the combination which gives us the lowest AIC. This method is computationally heavy, since we have to estimate the model by a hundreds of thousands of datapoints. However, it guarantees that the result parameters is optimal, namely it maximizes the likelihood to the dataset.

Algorithm 1 ARIMA(p,d,q) parameters select

1: **procedure** PARAMS SELECT($trainset, maxP, maxD, maxQ$)
2:      $MinAIC \leftarrow \infty$
3:      $OptimalModel \leftarrow None$
4:      **for** $p = 1$ to $maxP$ **do**
5:         **for** $d = 0$ to $maxD$ **do**
6:            **for** $q = 1$ to $maxQ$ **do**
7:               $Model \leftarrow$ `ARIMA(p,d,q)`
8:               $EstModel \leftarrow$ Estimate coefficients α_i of $model$ by $trainset$
9:               **if** $EstModel.AIC < MinAIC$ **then**
10:                  $MinAIC \leftarrow EstModel.AIC$
11:                  $OptimalModel \leftarrow EstModel$
12:               **end if**
13:            **end for**
14:         **end for**
15:      **end for**
16:      **return** $optimalModel$
17: **end procedure**

Running the algorithm on Trainset gives the following optimal parameters.

	Open	High	Low	Close
P	1	2	1	1
D	1	1	1	1
Q	18	25	26	18
AIC	-1.43336e+05	-1.44620e+05	1.45923e+05	-1.43399e+05

Table 1: Optimal parameters and AIC

4.3   VAR(p)

4.3.1   Model description

VAR is applied to multivariate data. It is similar to $AR(p)$ model; however, instead of considering $\{x_t\}$ as real values (univariate), we analyse $\{\mathbf{x_t}\}$ as a timeseries of vectors $\mathbf{x_i} = (x_i^O, x_i^H, x_i^L, x_i^C)$. Formally, a timeseries $\{\mathbf{x_t}\}$ in which $\mathbf{x_i}$ is a row vector of n dimensions, is $VAR(p)$ if

$$\mathbf{x_t} = \beta_1 \mathbf{x_{t-1}} + \ldots \beta_p \mathbf{x_{t-p}} + e_t$$

where e_t is discrete white noises and β_i is a column vector of n dimensions.

4.3.2   Parameters selection

Parameters selection for VAR(p) is done in the same way as ARIMA(p,d,q): we loop through a set of possible parameters to find the one with lowest AIC.

Algorithm 2 VAR(p) parameters select

1: **procedure** PARAMS SELECT($trainset, maxP$)
2:      $MinAIC \leftarrow \infty$
3:      $OptimalModel \leftarrow None$
4:      **for** $p = 1$ to $maxP$ **do**
5:          $model \leftarrow$ VAR(p)
6:          Estimate coefficients of $model$ by $trainset$
7:          **if** Estimated model has lower AIC **then**
8:              $MinAIC \leftarrow model.AIC$
9:              $OptimalModel \leftarrow model$
10:         **end if**
11:     **end for**
12:     **return** $OptimalModel$
13: **end procedure**

Running the algorithm on Trainset gives the following optimal parameters $P = 20$ with $AIC = -1.053747548995608e + 07$

5 Deep Learning Model

5.1 Recurrent Neural Network

Recurrent Neural Network (RNN) is introduced by [4] to process sequential input. In RNN, each state connects to the followed state to form a directed graph. The structure of RNN makes it capable of handling sequential data with temporal dynamic behaviour. RNN has been widely used in timeseries prediction and natural language processing.

However, due to the nature of network topology, Hochreiter [**?**] showed that Recurrent Neural Network has *vanishing gradient* and *exploding gradient* problems. Let

5.2 Long-Short Term Memory

Hochreiter and Schmidhuber (1997) [1] introduced Long-Short Term Memory neural network architecture architecture to solve both vanishing gradient and exploding gradient problem from RN

5.3 Proposed Network Topology

Our survey on the data implies that significant autocorrelation may appears even further than 20 timesteps into the past. In our proposed network topology, we

add more hidden units into each LSTM layers, so that the network can learn from data points of higher lags.

5.4 Training

Training data for LSTM network must be prepared in a different way than for ARIMA or VAR. From the train set, we make 2 We train the model by optimizer *adam*, with batch size 32. Other parameters can be found in the source code. As we can see from training progress, after the second epoch, the loss does not decrease any more, meanwhile the

6 Experiments

6.1 Description

We consider using LSTM network in two experiments. In the first experiments, we build and train the network to predict future values only by giving to history lags of one timeseries *(univariate)*. For example, we train the network to predict one Open price value in the future given only the Open prices in the past. This experiment is designed to compare the performance of LSTM with $ARIMA(p,d,q)$ model.

In the second experiments, we build and train the network so that it would predict one values ahead of one feature (e.g. one value of Open price ahead), given history values of *all* features in the past. This experiment is designed to compare the performance of LSTM to $VAR(p)$ model.

In both experiments, since we want to predict the future values of all Open, High, Low and Close features, we have to build and train one mode for each feature accordingly. Therefore, in each experiment we have to build and train 4 models.

6.2 Univariate Experiment

6.2.1 Results from ARIMA(p,d,q)

	Open	High	Low	Close
P	1	2	1	1
D	1	1	1	1
Q	18	25	26	18
RMSE on Test set	0.000377785	0.00035527	0.00036089	0.00037367
MAPE on Test set	0.021241	0.019921	0.020236	0.021091
Overall MAPE	0.000367018			
Overall RMSE	0.020622			

Table 2: Optimal parameters and error on Test set

These following figures are the visualization of results.
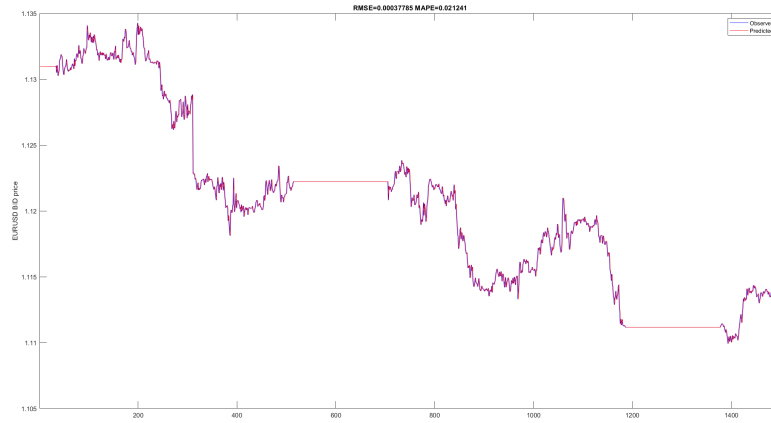
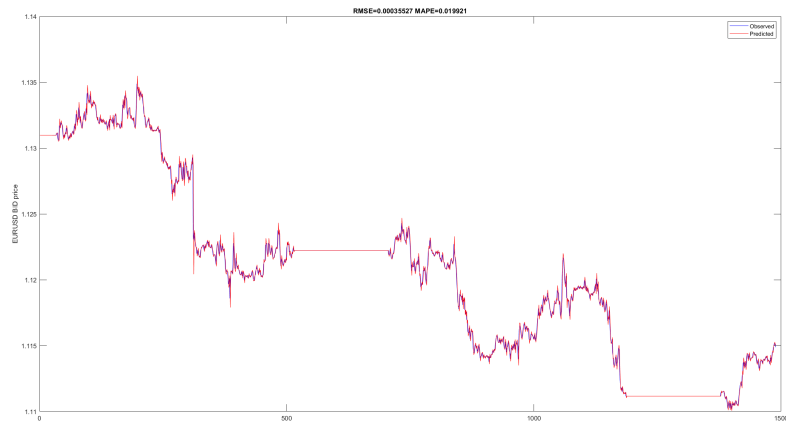Figure 2: ARIMA(1,1,18) on Open price.
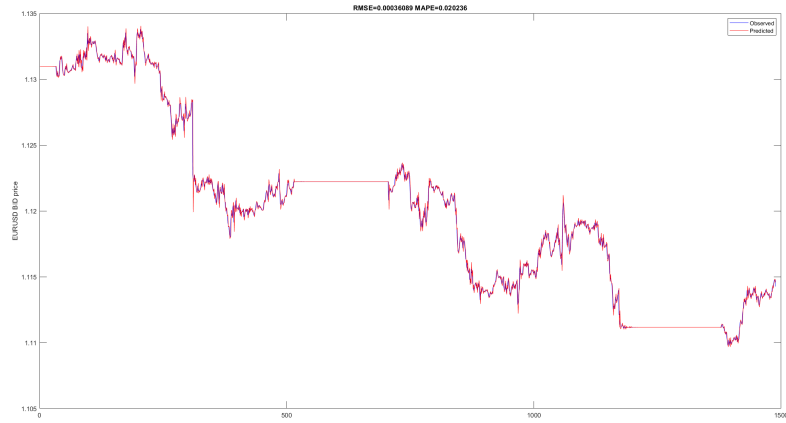

Figure 3: ARIMA(2,1,25) on High price.
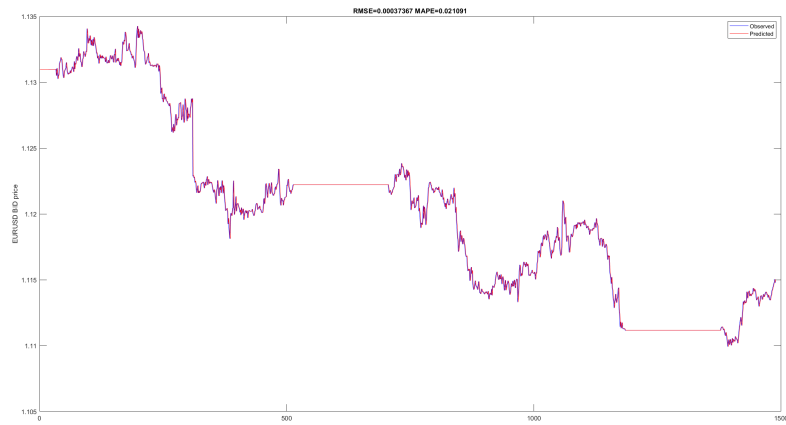
Figure 4: ARIMA(1,1,26) on Low price.

Figure 5: ARIMA(1,1,18) on Close price.

6.2.2 Results from LSTM
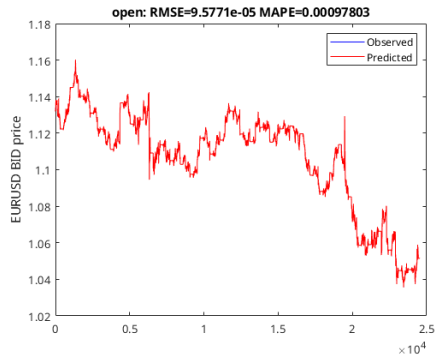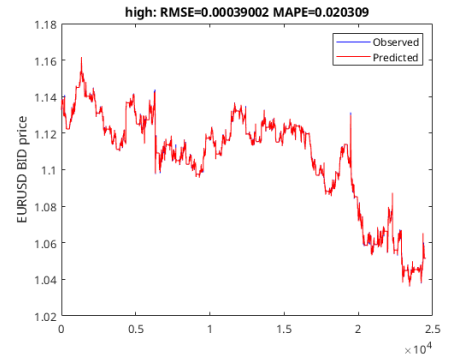
6.3 Multivariate

6.3.1 Results from VAR(p)

P=20	Open	High	Low	Close
RMSE on Test set	0.000095771	0.00039002	0.00037809	0.00053147
MAPE on Test set	0.00097803	0.020309	0.019355	0.027689
Overall MAPE	0.0003829817534299121			
Overall RMSE	0.0170827575			

Table 3: Optimal parameters and error on Test set

(a) Open

(b) High
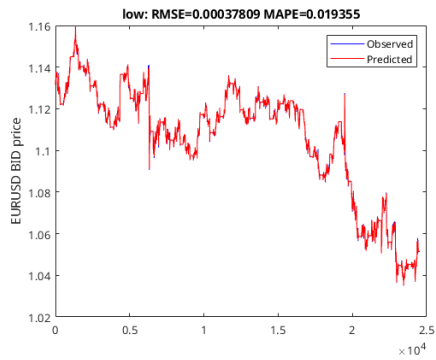
(c) Low
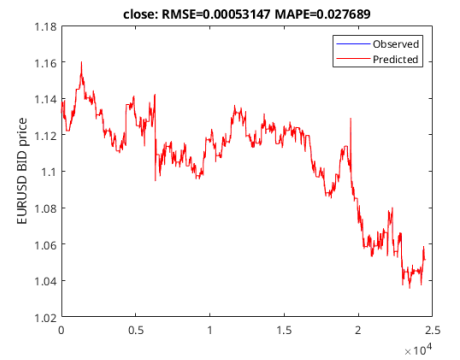
(d) Close

Figure 6: Prediction on Test set.

Since *VAR(20)* fits the test set very well, for visualization, we draw an additional plot for values 500-600 to highlights the minute differences between prediction and actual observation.
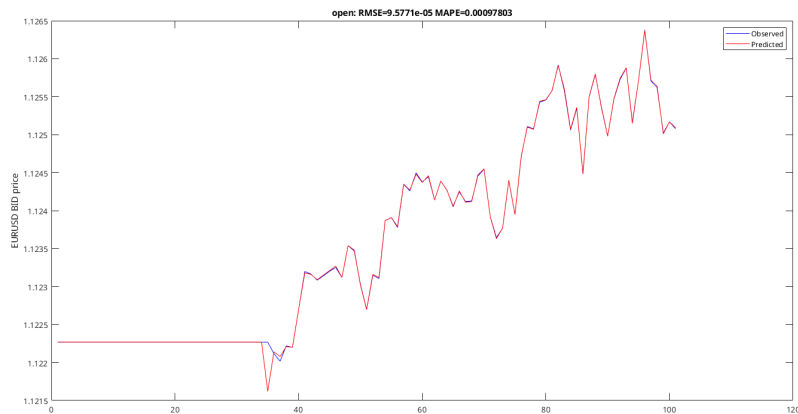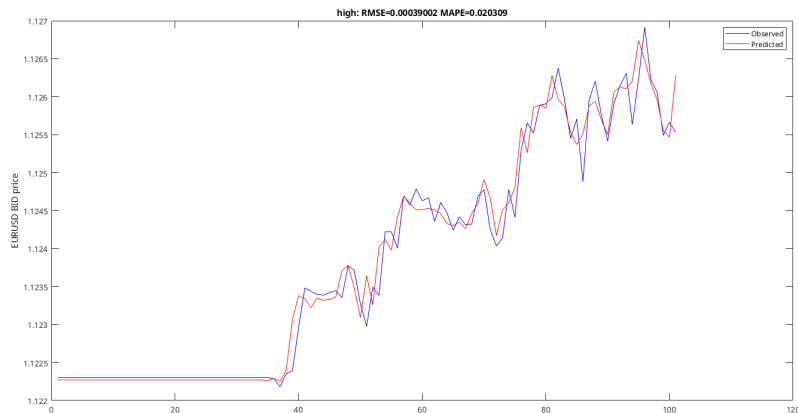

Figure 7: ARIMA(1,1,18) on Open price.
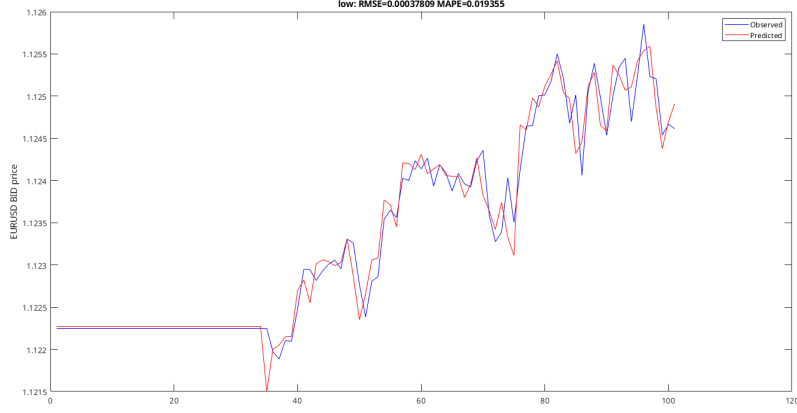

Figure 8: ARIMA(2,1,25) on High price.
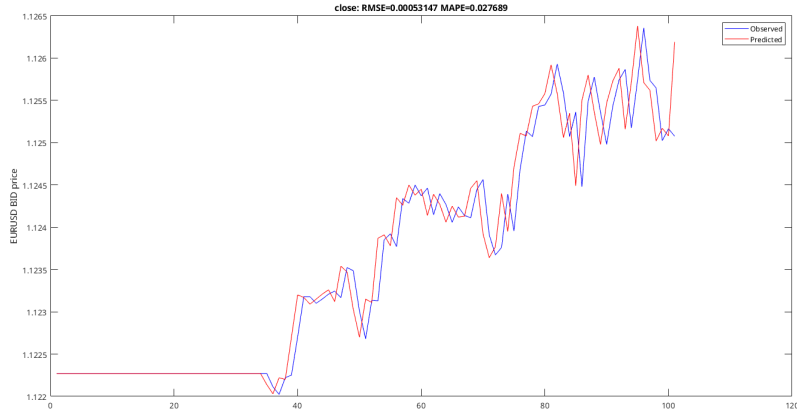
Figure 9: ARIMA(1,1,26) on Low price.

Figure 10: ARIMA(1,1,18) on Close price.

6.3.2 Results from LSTM

7 Conclusion

As the results have shown, ...

However, computational effort spent for training LSTM deep learning model is much higher than ARIMA and VAR. Furthermore the, adding components to neural network topology results in higher computational cost.

References

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