UDC 004.93

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NON-STATIONARY TIME SERIES PREDICTION USING ONE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK MODELS

Annotation. *The main goal of non-stationary time series prediction is the construction, identification, configuration and verification of their models. The efficiency of using machine learning technologies for the analysis of non-stationary time series is shown due to their ability to model complex nonlinear dependencies in the behaviour of the time series from both depending on previous values and external factors, to analyse features, relationships and complex interactions. The features of time series prediction using a one-dimensional convolutional neural network are discussed. The features of the architecture and the training process when using a one-dimensional convolutional neural network are considered on the example of solving the problems to predict sales and build a forecast of company stock prices. To improve the quality of the prediction, the initial time series were pre-processed by the moving average method in the window. Computer modelling of the predicting problem using the one-dimensional convolutional neural network was performed in the Python programming language. The sales prediction using the proposed one-dimensional convolutional neural network model predicted volume sale of cars and commercial vehicles in Vietnam from two thousand and eleven to two thousand and eighteen. The one-dimensional convolutional neural network model has given a high accuracy of prediction with seasonal trend data. In stock prices prediction, another architecture of one-dimensional convolutional neural network model was launched, which corresponds to non-stationary data with large lengths of data series with small intervals between minutes, such as stock trading statistics per minute. In this project, data is taken from Amazon Nasdaq one hundred for forty thousand five hundred and sixty data points. The data is divided into training and test sets. The test suite is used to verify the actual performance of the model. It is shown that the model of a one-dimensional convolutional neural network gives good results in the presence of both seasonal and trend components of the time series with large data sizes.*

Keyword: *time series; time series prediction; deep learning; one-dimensional convolutional neural network*

Introduction

Time series prediction is one of the most important applied problems that have been solved by intelligent information systems with the aim of most accurately predicting the behaviour of various factors in trade and financial activity, in technology, meteorology and geology, and many others [1].

The main goal of time series prediction is the construction, identification, configuration and verification of their models. As a rule, statistical analysis methods developed in the 60-70s of the XX century in the works of J. Box, G. Jenkins and others are used for this [2].

Despite the fact that these methods have shown their effectiveness in practice at present for solving the forecasting problem (especially in conditions of noise or gaps, with unsteady and multidimensional data, long data sequences), methods based on machine learning technologies are increasingly being used, especially neural networks.

Machine learning technologies make it possible to model complex nonlinear dependences in the behaviour of the time series from both previous values and external factors, and analyse features, relationships, and complex interactions [3-8]. An important requirement when choosing a machine learning technology is the availability of memory about previous properties of the time series. With this in mind, time series prediction uses a modern kind of machine learning technique

– Deep Learning, which applies deep neural network architectures to solve various complex problems [9-11]. Deep learning neural networks are able automatically learn and extract features from raw data. This feature of neural networks can be used for time series forecasting problems, where models can be developed directly on the raw observations without the direct need to scale the data using normalization and standardization or to make the data stationary by differencing. Therefore, new types of neural networks, such as long-short term memory (LSTM) – variant of the recurrent neural network and convolutional neural networks (CNN), show good results for predicting time series [12; 15].

Despite the fact that CNN is a very popular type of neural networks for classifying images, it should be noted that CNNs are becoming an increasingly important concept in computer science and are finding more and more applications including in time series forecasting [16-18]. As the analysis of literary sources has shown, for time series prediction it is advisable to use one-dimensional convolution networks (1D CNN). The 1D CNN model extracts a feature from a sequence data and maps the internal features of the sequence. A 1D CNN is very effective for receiving feature from a fixed-length segment of the overall dataset, where it is not so important, where the feature is located in the segment. Using one-dimensional convolutional neural networks have given good results when analysing the time series obtained from measuring sensors and analysing signal data over a fixed-length period, for example, fragments of an audio recording.

The purpose of this article is to obtain time series models using one-dimensional convolutional neural network for providing acceptable prediction accuracy.

Two research objectives survey problems using 1D CNN, which are reviewed in this article, are sale prediction and stock price prediction.

Sale prediction [4-5; 19-20] is an important part of modern business intelligence. It can improve the planning of production processes as well as inventory management practices. In particular, the fast growth of enterprises and their incursion into new markets make inventory optimization necessary. Even more, sales do not only summarize the sold quantity, but they also include information that reflects changes in consumer's behaviour concerning the selling prices. Regarding the quantity of data required to estimate demand trends, there is an active discussion in the literature focused on determining the optimal size of a dataset for demand forecasting [4-5; 19-20].

Stock market prediction [6-8; 14-15; 21] is the act of trying to determine the future value of a company stock or other financial instrument traded on a financial exchange. The successful prediction of a stock's future price will maximize investor's gains.

1. Preliminary notes

To improve the quality of the prediction, the initial time series are pre-processed by the moving average method in the window [5]. The width of the sliding window L can be varied to include more or less previous time steps (or time points) depending on the specificity of the dataset and the user preference. The presentation scheme of test and forecast data is presented in Fig. 1. Input data of the NN model for predicting – N values of the initial time series in the training sample.

Python programming language was used to conduct the simulation. Today, Python is considered the preferred language for teaching and learning machine learning technologies. Python is growing and may become the dominant platform for applied machine learning. Although the main reason for justifying the adoption of Python for time series forecasting is that it is a general-purpose programming language that can be used for both research and production.

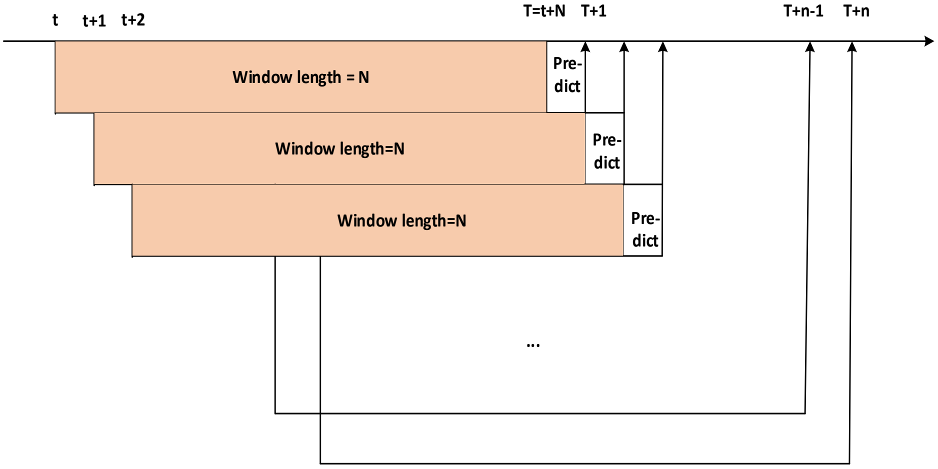


Fig. 1. Setting window length, predicted length and sliding window during the whole sample period

Python library for time series SciPy is an ecosystem of Python libraries for mathematics, science, and engineering [16; 22-26]. It is an add-on to Python that you will need for time series prediction .Two SciPy libraries provide a foundation for most others; they are NumPy for providing efficient array operations and Matplotlib for plotting data. There are three higher-level SciPy libraries that provide the key features for time series forecasting in Python. They are pandas, statsmodels, and scikit-learn for data handling, time series modeling, and machine learning respectively.

Two of the most common metrics, which used to measure accuracy for continuous variables, are mean absolute error (MAE) and root mean squared error (RMSE) are [2-3; 22].

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction – $\hat{y}_j$ and actual observation $-y_j$, where all individual differences have equal weight

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|. \quad (1)$$

Root mean squared error (RMSE) [2-3; 5] is a quadratic scoring rule that also measures the average magnitude of the error. It's the square root of the average of squared differences between prediction and actual observation

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}. \quad (2)$$

The Mean Squared Error (MSE) [22-23], loss is the default loss to use for regression problems. Mean squared error is calculated as the average of the squared differences between the predicted and actual values. The result is always positive regardless of the sign of the predicted and actual values and a perfect value is 0. The squaring means that larger mistakes result in more error than smaller mistakes, meaning that the model is punished for making larger mistakes. The mean squared error loss function can be used in Keras by specifying "*mse*" or "*mean_squared_error*" as the loss function when compiling the model.

2. Features of the CNN's architecture

CNN were developed with the idea of local connection, which is achieved by replacing weighted sums from the neural network with convolutions [9; 15-16]. In each CNN layer, the input data is convoluted with a weight matrix (for example, a filter) to create a map of objects. All values in the output map are the same weight, so that all nodes in the output signal detect one and the same. Total CNN quantity of weights is reducing. This leads to more effective training and study in each layer of the weight matrix, which is able to capture the necessary translation-invariant features from the input data.

There are three main types of layers in the basic architecture of CNN: a convolutional layer, a pool layer, and a fully connected layer (Fig. 2).

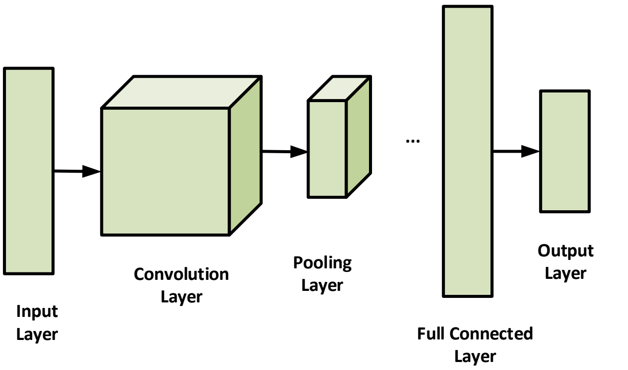


Fig. 2. Basic architecture of CNN

In the first layer, this input is convolved with a set of filters M_1 applied to all input channels $x = (x_t)_{t=0}^{N-1}$. With the given classification tasks and the model with parameter values, the task for the classifier is to derive the predicted class based on the input time series $x(0), \dots, x(t)$.

The output map of objects from the first convolution layer is then convolved with a filter w_h^1

$$a^1(i,h) = \left(w_h^1 * x\right)_i = \sum_{j=-\infty}^{\infty} w_h^1\,(j)x(i-j),$$

where: $w_h^1 \in R^{1\times k\times 1}$and $a^1 \in R^{1\times N-k+1\times M_1}$; i–the index of the feature map at the second dimension $(i = 1, \dots, N-k+1)$; h– the index of the feature map at the third dimension $(h = 1, \dots, M_1)$.

In each subsequent layer$l = 2, \dots, L$, the input feature map $f^{l-1} \in R^{1\times N_{l-1}\times M_{l-1}}$is convolved with a set of M_l filters $w_h^l \in R^{1\times k\times M_{l-1}}$, $h = 1, \dots, M_l$, to create a feature map $a^l \in R^{1\times N_l\times M_l}$,

$$a^l(i,h) = \left(w_h^l * f^{l-1}\right)_i$$
$$= \sum_{j=-\infty}^{\infty}\sum_{m=1}^{M_{l-1}} w_h^1(j,m)f^{l-1}(i-j,m).$$

The obtained value is subjected to nonlinear transformation $f^l = \varphi(a^l)$.

Thus, the filter controls the receptive field of each output node. Then the output goes to a pool (usually a layer with a maximum pool), which acts as a subsample layer

$$p^l(i,h) = max_{r\in R}(f^l(i\times T + r, h)),$$

where: R – the pooling size; T – the pooling stride; i– the index of the resultant feature map at the second dimension.

Thus, the trained model helps minimize the error between the output from the network and the true output that we are interested, which is often denoted as the objective function (loss function).

3. Univariate 1D CNN model for sale prediction

Data preparation

The dataset, which was used in the task sale prediction, is the database of cars and commercial vehicles (CCV) sale in per month from January 2011 to December 2018 in Vietnam (Fig. 3) [27].

All data is saved in file "*Sales_CCV_Vietnam _2009_2019.csv"*. Descriptive statistics of this data set are created (Table 1). The length of the test sample N is 24 months, the sliding window is 1 month, and the predicted period is 12 months (monthly). This means that we forecast a sale in 12 months by looking at the data for the previous 24 months, based on the monthly current time.

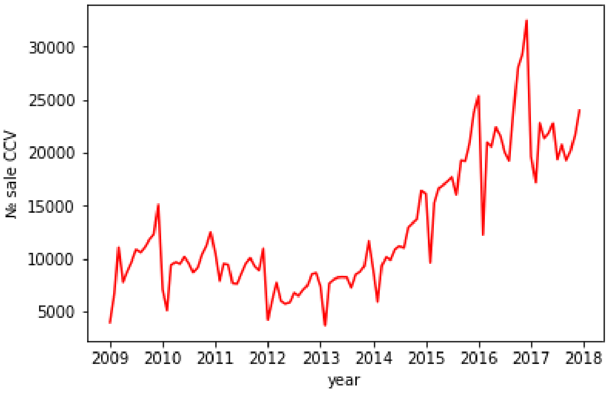


Fig. 3. Graphical representation time series of the volume sales per month of CCV in Vietnam for 8 years

The presented time series has the following characteristics:

– seasonality, i.e. periodicity of the structure, which may be associated with a calendar day, month, quarter etc.;

– trend;

– volume sales are higher in the winter months than in the spring. This is usually due to the fact that usually in Vietnam more purchases are concentrated in the last months of the year, before the lunar New Year.

Table 1. Descriptive statistics of CCV time series

Name	Volume sale of CCV in Vietnam (2011-2018)
Count (months)	96
mean	14867
std	7082
min	3679
25 %	8533
50 %	13132
75 %	21053
max	32511

1D CNN Architecture

1D CNN architecture for sale prediction (Fig. 4) was used as 3 layers convolutional neural network (combination of convolution and max-pooling layers) with one fully-connected layer. The summary representation shows the features of 1D CNN model (Table 2). It should be noted that the presence of the third convolutional level MaxPooling1D (with pool size=2) allows the model to learn more complex features. The last layer is a fully connected layer (Dense in Keras). It uses a 'Relu' activation function to produce a probability distribution over the output classes.

Learning Model Details

In training 1D CNN, the following parameters were used: batch size = 200, epochs =30000, optimize = 'adam', loss function = 'mse', metrics = 'mae'.

The graphs obtained by training the sales predicting model in 1D CNN for the absolute learning error – MAE and the learning loss function – MSE are shown in Fig. 5.

The results of the calculation of the predicting error using the 1D CNN prediction sale model showed, that it does not exceed 1 %.

For example, the results obtained using the developed 1D CNN model for predicting CCV sales in January – December 2017 in Vietnam are shown in Fig. 6 and Table 3.The predicted error from January 2017 to November 2017 does not exceed 0.9 %. In December 2019, the predicted error is 17.9 %. This large discrepancy can be explained by the sudden drop in sales due to changes in import tax, environment tax and traffic laws for car users, which were enacted since November 2017.

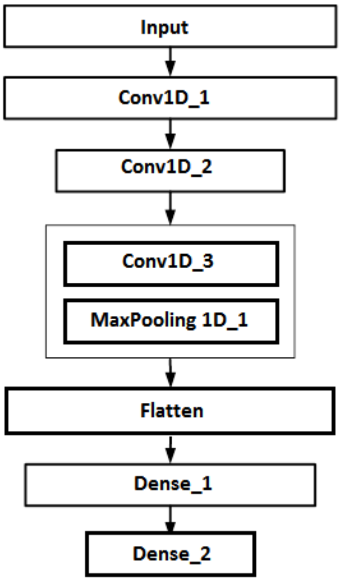
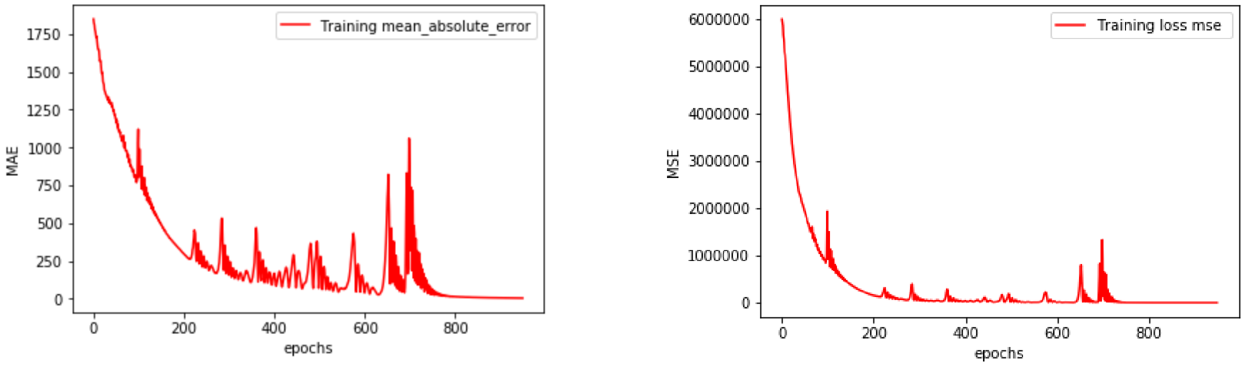


Fig. 4. 1D CNN general architecture for sale prediction

Table 2. Summary representation of 1D CNN

Layers	Hyper-parameter	
Conv1D_1	Unit	17
	No. of filter	256
	Kernel size	8
	Activation Function	ReLu
Conv1D_2	Unit	10
	No. of filter	256
	Kernel size	8
	Activation Function	ReLu
Conv1D_3	Unit	3
	No. of filter	256
	Kernel size	8
	Pooling size	2
	Activation Function	ReLu
Flatten	Unit	256
Dense_1	Unit	100
	Activation Function	ReLu
Dense_2	Unit	1



a

b

Fig. 5. Graphs of training mean absolute error (a) and training loss (b) in training process of 1D CNN model of sale prediction

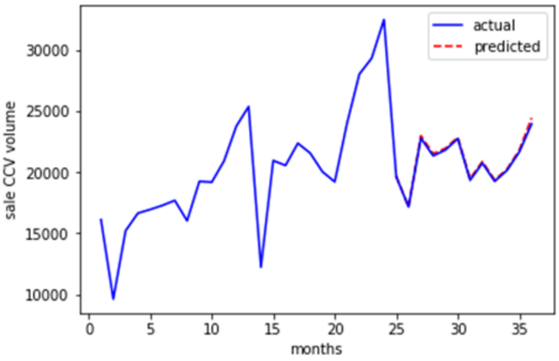


Fig. 6. Prediction results using 1D CNN to predict CCV sales in Vietnam

Table 3. Prediction results of CCV sales in January – December 2017 in Vietnam

Months in 2018	Actual (A)	Predicted (P)	MAE$_i$	MAE$_i$ /A,%
January	19619	19668	49	0.20
February	17156	17171	15	0.09
March	22792	22995	203	0.89
April	21345	21524	178	0.83
May	21829	21963	135	0.62
June	22750	22876	126	0.55
July	19345	19484	138	0.71
August	20746	20881	135	0.65
September	19257	19370	113	0.58
October	20156	20256	100	0.40
November	21662	21814	152	0.70
December	23963	19668	4295	17.90

4. Univariate 1D CNN model for stock price prediction

Data Preparation

A financial time series is a collection of prices such as stock, currency and commodity, obtained sequentially in time (Fig. 7). The data for this model is collected from trading data minute by minute of AMZN from Nasdaq 100 [28].

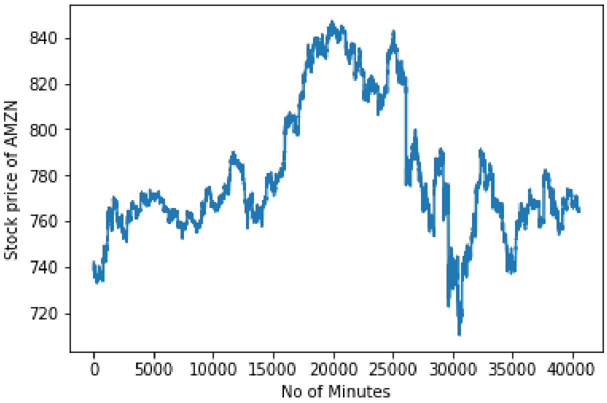


Fig. 7. Graphical representation of the time series AMZN stock data from the Nasdaq 100

Descriptive statistics that summarize the central trend, variance, and distribution form of the dataset is shown in Table 4. We used the 12800 data points as training data; 2560 as testing data. The window length (as in Fig. 1) was set to 128 minutes, the sliding window to 1 minute, and the predicted period to N minutes. This means that we predict the stock price in n minutes, looking at the data for the previous 128 minutes, based on the current minute point in time.

Table 4. Descriptive statistics of AMZN stock data time series

Name	Stock data from Nasdaq100
count(minutes)	40560
mean	780
std	29
min	710
25 %	762
50 %	770
75 %	797
max	847

1D CNN's Architecture for Stock price prediction

The architecture of the 1D CNN model for predicting stock prices is similar to the previous one, which is used in sales prediction (Fig. 4). However, there are some differences, namely:

– the first layer of the model is a fully connected layer (Dense in Keras), using the "ReLu" activation function to obtain the probability distribution by input classes;

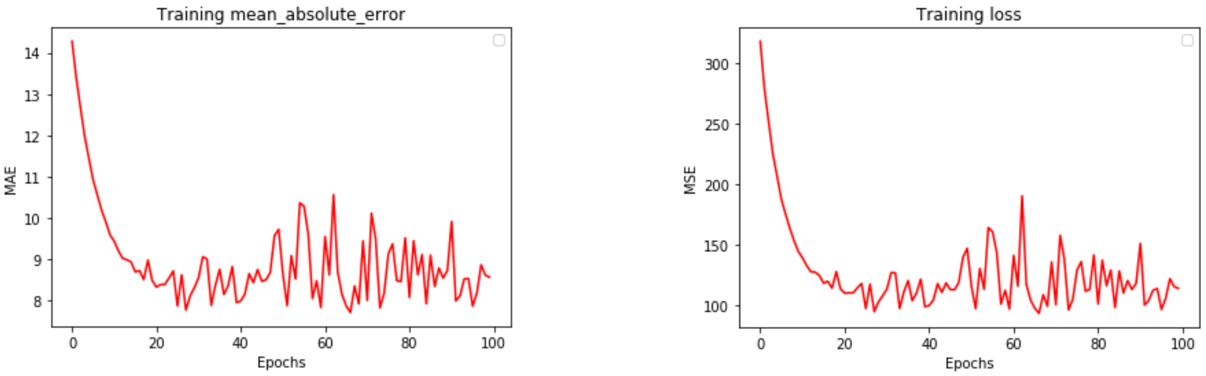
– the dimensions of the resulting layer are large enough, so each convolutional layer is connected to the MaxPooling1D layer so that the model reduces the size of the layer nodes and can study more complex features;

– the ranges of differences between the time intervals of the series are not very large, and the length of the time series is large, then using 2 convolutional layers (not 3 layers as in the model shown in Fig. 4), the analysis and preservation of the characteristics of the processed time series are quite guaranteed, and it doesn't require a lot of network learning time. The first convolution layer 1D with 128 feature detectors (core size 1 is applied to each feature detector). The second 1D convolutional layer with 64 filters (core size 1).

Learning Model Details

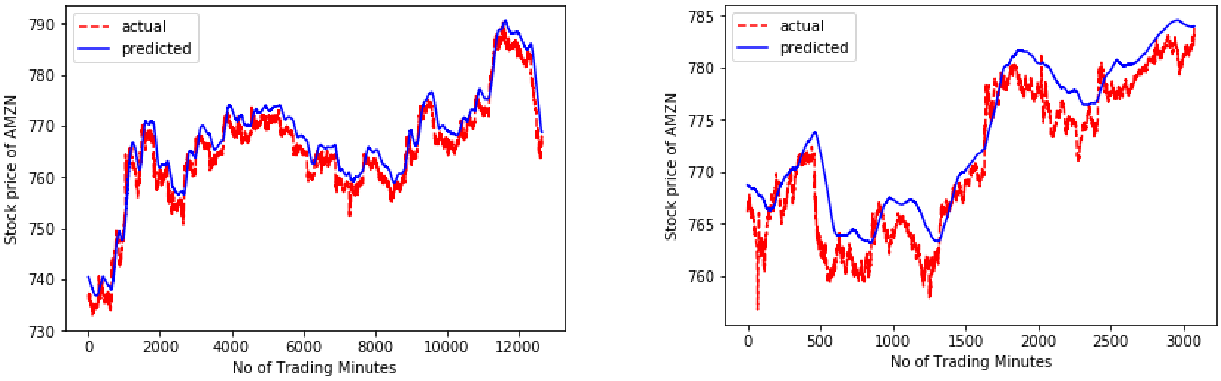
When training 1D CNN, the following parameters were used: batch size=200, epochs=100, optimize= 'adam', dropout rate=0.2, loss function= 'mse', metrics= 'mae'. An optimization algorithm "Adam" is used in training process and for different parameters an adaptive learning rates are computed. To prevent the over-fitting in this network a regularization method "Dropout" is used. Dropout rate represents the percentage of nodes dropped for each iteration and sample during training. The graphs obtained by training the stock price prediction model in 1D CNN for training mean absolute error "mae" and training loss "mse" are shown in Fig. 8.

It should be noted that the 1D CNN model showed good results in predicting stock prices both on the training (Fig. 9a) and test samples (Fig. 9b). On the training sample, the average absolute error (MAE) and the standard error (RMSE) were 2.72 and 3.09, respectively, and on the test 2.93 and 3.96.



a b

Fig. 8. The graphs of training mean absolute error (a) and training loss (b) in training process of 1D CNN model of stock price prediction



a b

Fig. 9. Graphs of obtained results using the 1D CNN stock price predicting model for the training (a) and for the test sample (b)

Conclusions

The article shows the possibility of using the 1D CNN model for one-factor forecasting of time series for the task of predicting car sales in Vietnam and predicting stock prices. It is shown that the 1D CNN model gives good results in the presence of the seasonal and trend components of the time series.

In the stock price prediction the more complex architecture of the 1D CNN model was used. This made it possible to take into account the non-stationary nature of the data and the significant size. In this project, the data is taken from Amazon's Nasdaq 100 padding of 40560 data point. The data is divided into training set (12800 data point) and testing set (2560 data point). Average of trading stock price in 13560 minutes is 780. Training sets are used during the learning process of the model. The obtained results are RMSE = 3.09 and MAE = 2.72. Testing set is used as data to test actual model performance. The result obtained when predicting stock price with testing set is RMSE = 3.96 and MAE = 2.93.

From the obtained results, we can see 1D CNN models work well for non-stationary time series prediction. In future work we will continue to explore multivariate time series prediction for data from stock, Forex. Currently RNN, LSTM models also yield good predictive results [29]. We will propose a hybrid model from 1D CNN and RNN, LSTM neural networks for predicting better result.

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Received.	29.11.2019
Received after revision	27.12.2019
Accepted	17.01. 2020

УДК 004.93

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ПРОГНОЗУВАННЯ НЕСТАЦІОНАРНИХ ЧАСОВИХ РЯДІВ З ВИКОРИСТАННЯМ ОДНОВИМІРНИХ ЗГОРТКОВИХ НЕЙРОННИХ МЕРЕЖ

Анотація. *Основною метою прогнозування нестаціонарних часових рядів є побудова, ідентифікація, налаштування і перевірка їх моделей. Показана ефективність використання технологій машинного навчання для аналізу нестаціонарних часових рядів завдяки їх здатності моделювати складні нелінійні залежності в поведінці часового ряду, як в залежності від попередніх значень, так і зовнішніх чинників, аналізувати особливості, відносини і складні взаємодії. Обговорено особливості прогнозування часових рядів з використанням одновимірної згорткової нейронної мережі. Розглянуто особливості архітектури і процесу навчання при використанні одновимірної згорткової нейронної мережі на прикладі рішення задач прогнозування продажів і побудови прогнозу цін акцій компанії. Для поліпшення якості прогнозу, вихідні часові ряди під давалися попередній обробці методом ковзного середнього в вікні. Комп'ютерне моделювання задачі прогнозування із застосуванням одновимірної згорткової нейронної мережі виконано на мові програмування Python. У прогнозі продажів з використанням архітектури запропонованої моделі одновимірної згорткової нейронної мережі зроблено прогноз продаж легкових і комерційних автомобілів у В'єтнамі в період з дві тисячі одинадцятого по дві тисячі вісімнадцятий роки. Модель одновимірної згорткової нейронної мережі показала високу точність прогнозування з даними сезонного тренду. У прогнозуванні цін на акції була використана інша архітектура моделі одновимірної згорткової нейронної мережі, яка відповідає нестаціонарним даним з великими довжинами серій даних при невеликому інтервалі між відліками, такими як дані статистики торгівлі акціями за хвилину. У цьому проекті дані взяті з AmazonNasdaq100 для сорока тисяч п'ятисот шістдесяти точок даних. Дані поділяються на навчальний і тестовий набори. Тестовий набір використовується для перевірки фактичної продуктивності моделі. Показано, що модель одновимірної згорткової нейронної мережі дає хороші результати при наявності як сезонної, так і трендової складових часового ряду при великих розмірах даних.*

Ключові слова: *часовий ряд; прогнозування часових рядів; глибоке навчання; одновимірна згорткова нейронна мережа*

УДК 004.93

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ПРОГНОЗИРОВАНИЕ НЕСТАЦИОНАРНЫХ ВРЕМЕННЫХ РЯДОВ С ИСПОЛЬЗОВАНИЕМ ОДНОМЕРНЫХ СВЕРТОЧНЫХ НЕЙРОННЫХ СЕТЕЙ

Аннотация. *Основной целью прогнозирования нестационарных временных рядов является построение, идентификация, настройка и проверка их моделей. Показана эффективность использования технологий машинного обучения для анализа нестационарных временных рядов благодаря их способности моделировать сложные нелинейные зависимости в поведении временного ряда, как в зависимости от предыдущих значений, так и внешних факторов, анализировать особенности, отношения и сложные взаимодействия. Обсуждены особенности прогнозирования временных рядов с использованием одномерной сверточной нейронной сети. Рассмотрены особенности архитектуры и процесса обучения при использовании одномерной сверточной нейронной сети на примере решения задач прогнозирования продаж и построения прогноза цен акций компании. Для улучшения качества прогноза, исходные временные ряды подвергались предварительной обработке методом скользящего среднего в окне. Компьютерное моделирование задачи прогнозирования с применением одномерной сверточной нейронной сети выполнено на языке программирования Python. В прогнозе продаж с использованием архитектуры предложенной модели одномерной сверточной нейронной сети спрогнозировано продажу легковых и коммерческих автомобилей во Вьетнаме в период с две тысячи одиннадцатого по две тысячи восемнадцатый годы. Модель одномерной сверточной нейронной сети показала большую точность предсказания с данными сезонного тренда. В прогнозировании цен на акции была использована другая архитектура модели одномерной сверточной нейронной сети, которая соответствует нестационарным данным с большими длинами серий данных при небольшом интервале между отсчетами, такими как данные статистики торговли акциями за минуту. В этом проекте данные взяты из*

AmazonNasdaq100 для сорока тысяч пятьсот шестидесяти точек данных. Данные делятся на обучающий и тестовый наборы. Тестовый набор используется для проверки фактической производительности модели. Показано, что модель одномерной сверточной нейронной сети дает хорошие результаты при наличии как сезонной, так и трендовой составляющих временного ряда при больших размерах данных.

Ключевые слова: *временной ряд; прогнозирование временных рядов; глубокое обучение; одномерная сверточная нейронная сеть*

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