17. NEURAL NETWORKS: FORECASTING ECONOMIC TIME SERIES

Kadushkevich D.R.

Belarusian State University of Informatics and Radioelectonics
Minsk, Republic of Belarus

Ladyjenko M.V. – Senior Lecturer

The potential of machine learning techniques in the field of economic forecasting is presented in this paper. The use of Recurrent Neural Networks (RNNs) and their variants is described.

Economic forecasting is a challenging task that is vital to many industries and policy-making bodies. Accurate forecasts of economic time series can help businesses make informed decisions about investments, inventory, workforce planning, and can also help governments and central banks set monetary policy. Historically, economists have relied on statistical models such as autoregressive integrated moving average (ARIMA) and vector autoregression (VAR) to forecast economic variables. However, in recent years, there has been growing interest in using neural networks for such purposes, Recurrent Neural Networks (RNNs) specifically.

Time series forecasting is the process of using statistical or machine learning techniques to make predictions about future values of a time series, which is a sequence of data points ordered in time. Time series forecasting is commonly used in a variety of fields, including finance, economics, sales and marketing, weather forecasting, and many others. The goal of time series forecasting is to identify patterns and trends in the historical data that can be used to predict future values with a certain level of accuracy. This can help businesses and organizations make informed decisions based on anticipated future trends and events [1].

In the context of business and marketing operations, Recurrent Neural Networks (RNNs) can be utilized for a variety of applications. RNNs are a type of neural network commonly used for processing sequential data, such as time series, speech signals, and natural language. Unlike traditional neural networks, which process data inputs independently of one another, RNNs can take into account the context and history of a sequence of inputs [2].

RNNs have a recursive structure that allows them to use the output of previous time steps as input to the current time step, forming a feedback loop. This feedback loop enables the RNN to maintain a state or memory of what has been seen so far, which can be useful for tasks such as predicting the next element in a sequence, generating sequences, or processing natural language.

For business purposes, RNNs can be used in a variety of applications. For example, RNNs can be used to predict sales or customer behavior based on past data, which can help businesses make more informed decisions about inventory management, marketing strategies. RNNs can also be used to generate product descriptions or marketing messages, which can save time and improve the consistency of messaging.

Additionally, RNNs can be used for natural language processing tasks such as sentiment analysis, where the goal is to determine the overall sentiment of a text (e.g., positive, negative, or neutral). This can be useful for monitoring customer feedback or social media sentiment about a brand.

To use RNNs in practice, businesses typically need to have a large amount of historical data to train the neural network. The RNN is then trained on this data to learn patterns and relationships that can be used for prediction or generation tasks. Once the RNN is trained, it can be used to make predictions or generate new sequences based on new input data.

However, standard RNNs can suffer from the problem of vanishing gradients, where the gradients become extremely small or zero, making it difficult to learn long-term dependencies. To address this issue, variants of RNNs have been developed, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) networks, which have gating mechanisms that selectively update or forget information based on the input [1]. In-depth researches and comparisons of different models of RNNs infer that the GRU model outperforms the others, particularly for multivariate forecasting in an out-of-sample scenario. Therefore, the GRU model can be considered as the most effective and reliable model for this type of forecasting task [3].

The findings of this paper suggest that neural networks, specifically RNN and GRU, can be a valuable tool for forecasting economic and financial time series. This could have significant impact for businesses and organizations that rely on accurate predictions of economic variables to inform their decision-making processes, as well as for government agencies responsible for economic planning and regulation.

References:

1. What is time series data? [Electronic resource]. – Mode of access: https://www.influxdata.com/what-is-time-series-data/. – Date of access: 20.03.2023.
2. Neural Networks for Forecasting Financial and Economic Time Series [Electronic resource]. – Mode of access: https://medium.com/microsoftazure/neural-networks-for-forecasting-financial-and-economic-time-series-6aca370ff412. – Date of access: 20.03.2023.
3. Neural Networks for Financial Time Series Forecasting [Electronic resource]. – Mode of access: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9141105/. – Date of access: 20.03.2023.