

OPTIMISING LSTM AND BiLSTM MODELS FOR TIME SERIES FORECASTING THROUGH HYPERPARAMETER TUNING (Mengoptimumkan Model LSTM dan BiLSTM untuk Ramalan Siri Masa Melalui Penyesuaian Hiperparameter)

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ABSTRACT

Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) are the emerging Recurrent Neural Networks (RNN) widely used in time series forecasting. The performance of these neural networks relies on the selection of hyperparameters. A random selection of the hyperparameters may increase the forecasting error. Hence, this study aims to optimise the performance of LSTM and BiLSTM in time series forecasting by tuning one of the essential hyperparameters, the number of hidden neurons. LSTM and BiLSTM with 32, 64, and 128 hidden neurons and various combinations of other hyperparameters are formed in this study through grid searching. The models are evaluated and compared based on the Mean Squared Error (MSE) and Mean Absolute Error (MAE). The results from real data analysis revealed that 128 hidden neurons are the optimum choice of hidden neurons with the lowest error values. This study investigates whether BiLSTM, performs better than LSTM in forecasting. Thus, the performance of these two neural networks in forecasting time series data was compared, and the Wilcoxon-Signed Rank Test was conducted. Results revealed a significant difference in the performance of these two neural networks, and BiLSTM outperformed LSTM in forecasting time series data. Hence, BiLSTM with 128 hidden neurons is encouraged to be chosen over LSTM in time series forecasting. Since these findings have implications for future practice, the combination of model and hyperparameter should be chosen wisely to obtain more accurate predictions in time series forecasting.

Keywords: LSTM; deep learning; time series; forecasting; BiLSTM

ABSTRAK

Memori Jangka Pendek Panjang (LSTM) dan Memori Jangka Pendek Panjang Dwiarah (BiLSTM) ialah Rangkaian Neural Berulang (RNN) digunakan secara meluas dalam peramalan siri masa. Prestasi rangkaian neural ini bergantung pada pemilihan hiperparameter. Pemilihan rawak hiperparameter boleh meningkatkan ralat ramalan. Oleh itu, kajian ini bertujuan untuk mengoptimumkan prestasi LSTM dan BiLSTM dalam peramalan siri masa dengan menala salah satu hiperparameter penting, bilangan neuron tersembunyi. LSTM dan BiLSTM dengan 32, 64, dan 128 neuron tersembunyi dan pelbagai kombinasi hiperparameter lain dibentuk dalam kajian ini melalui carian grid. Model-model tersebut dinilai dan dibandingkan berdasarkan Ralat Purata Kuasa Dua (MSE) dan Ralat Mutlak Purata (MAE). Keputusan daripada analisis data sebenar mendedahkan bahawa 128 neuron tersembunyi adalah pilihan optimum neuron tersembunyi dengan nilai ralat terendah. Kajian ini mengkaji samada BiLSTM memberikan prestasi yang lebih baik berbanding LSTM dalam peramalan. Prestasi kedua-dua rangkaian neural ini dalam peramalan data siri masa dibandingkan, dan Ujian Peringkat Bertanda Wilcoxon (Wilcoxon-Signed Rank Test) dilaksanakan. Hasil kajian menunjukkan perbezaan ketara dalam prestasi kedua-dua rangkaian neural ini, dan BiLSTM mengatasi LSTM dalam peramalan siri masa. Oleh itu, BiLSTM dengan 128 neuron tersembunyi disarankan untuk dipilih berbanding LSTM dalam peramalan siri masa. Memandangkan penemuan ini mempunyai implikasi untuk amalan masa depan, kombinasi model dan hiperparameter harus dipilih dengan bijak untuk mendapatkan ramalan yang lebih tepat dalam peramalan siri masa.

Kata kunci: LSTM; pembelajaran mendalam; siri masa; ramalam; BiLSTM

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