Package ‘TSdeeplearning’

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Type Package

Title Deep Learning Model for Time Series Forecasting

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Description RNNs are preferred for sequential data like time series, speech, text, etc. but when dealing with long range dependencies, vanishing gradient problems account for their poor performance. LSTM and GRU are effective solutions which are nothing but RNN networks with the abilities of learning both short-term and long-term dependencies. Their structural makeup enables them to remember information for a long period without any difficulty. LSTM consists of one cell state and three gates, namely, forget gate, input gate and output gate whereas GRU comprises only two gates, namely, reset gate and update gate. This package consists of three different functions for the application of RNN, LSTM and GRU to any time series data for its forecasting. For method details see Jaiswal, R. et al. (2022). <doi:10.1007/s00521-021-06621-3>.

License GPL-3

Encoding UTF-8

LazyData true

RoxygenNote 7.2.1

Imports keras, tensorflow, reticulate, tsutils, BiocGenerics, utils, graphics, magrittr

Depends R (>= 2.10)

NeedsCompilation no

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\textbf{Data\_Maize} & \textit{Monthly International Maize Price Data} \\
\hline
\end{tabular}

\textbf{Description}

Monthly international Maize price (Dollor per million ton) from January 2010 to June 2020.

\textbf{Usage}

\begin{verbatim}
data("Data\_Maize")
\end{verbatim}

\textbf{Format}

A time series data with 126 observations.

\begin{verbatim}
price a time series
\end{verbatim}

\textbf{Details}

Dataset contains 126 observations of monthly international Maize price (Dollor per million ton). It is obtained from World Bank "Pink sheet".

\textbf{Source}


\textbf{References}


\textbf{Examples}

\begin{verbatim}
data(Data\_Maize)
\end{verbatim}
GRU_ts

**Gated Recurrent Unit Model**

**Description**

The GRU function computes forecasted value with different forecasting evaluation criteria for gated recurrent unit model.

**Usage**

```r
GRU_ts(xt, xtlag = 4, uGRU = 2, Drate = 0, nEpochs = 10, Loss = "mse", AccMetrics = "mae", ActFn = "tanh", Split = 0.8, Valid = 0.1)
```

**Arguments**

- `xt`: Input univariate time series (ts) data.
- `xtlag`: Lag of time series data.
- `uGRU`: Number of unit in GRU layer.
- `Drate`: Dropout rate.
- `nEpochs`: Number of epochs.
- `Loss`: Loss function.
- `AccMetrics`: Metrics.
- `ActFn`: Activation function.
- `Split`: Index of the split point and separates the data into the training and testing datasets.
- `Valid`: Validation set.

**Details**

The gated recurrent unit (GRU) was introduced by Cho et al.(2014). A GRU is part of a specific model of recurrent neural network that intends to use connections through a sequence of nodes to perform machine learning tasks associated with memory and clustering. Its internal structure is simpler and, therefore, it is also easier to train, as less calculation is required to upgrade the internal states. The update port controls the extent to which the state information from the previous moment is retained in the current state, while the reset port determines whether the current state should be combined with the previous information. Gated recurrent units help to adjust neural network input weights to solve the vanishing gradient problem that is a common issue with recurrent neural networks.
Value

TrainFittedValue
Training Fitted value for given time series data.

TestPredictedValue
Final forecasted value of the GRU model.

fcast_criteria
Different Forecasting evaluation criteria for GRU model.

References


See Also

LSTM, RNN

Examples

data("Data_Maize")
GRU_ts(Data_Maize)

LSTM_ts

Long-Short Term Memory Model

Description

The LSTM function computes forecasted value with different forecasting evaluation criteria for long-short term memory model.

Usage

LSTM_ts(xt, xtlag = 4, uLSTM = 2, Drate = 0, nEpochs = 10, Loss = "mse", AccMetrics = "mae", ActFn = "tanh", Split = 0.8, Valid = 0.1)

Arguments

xt Input univariate time series (ts) data.
xtlag Lag of time series data.
uLSTM Number of unit in LSTM layer.
Drate Dropout rate.
nEpochs Number of epochs.
Loss Loss function.
AccMetrics  Metrics.
ActFn  Activation function.
Split  Index of the split point and separates the data into the training and testing datasets.
Valid  Validation set.

Details

Long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) based RNN is designed to overcome the vanishing gradients problem while dealing with long term dependencies. In contrast to standard RNN, LSTM has this peculiar and unique inbuilt ability by maintaining a memory cell to determine which unimportant features should be forgotten and which important features should be remembered during the learning process (Jaiswal et al., 2022). An LSTM model analyses and captures both short-term and long-term temporal dependencies of a complex time series effectively due to its architecture of recurrent neural network and the memory function used in the hidden nodes.

Value

TrainFittedValue  Training Fitted value for given time series data.
TestPredictedValue  Final forecasted value of the LSTM model.
fcast_criteria  Different Forecasting evaluation criteria for LSTM model.

References


See Also

GRU, RNN

Examples

data("Data_Maize")
LSTM_ts(Data_Maize)
RNN_ts

Recurrent neural network Model

Description
The RNN function computes forecasted value with different forecasting evaluation criteria for recurrent neural network model.

Usage
```r
RNN_ts(xt, xtlag = 4, uRNN = 2, Drate = 0, nEpochs = 10,
Loss = "mse", AccMetrics = "mae", ActFn = "tanh",
Split = 0.8, Valid = 0.1)
```

Arguments
- `xt`: Input univariate time series (ts) data.
- `xtlag`: Lag of time series data.
- `uRNN`: Number of unit in RNN layer.
- `Drate`: Dropout rate.
- `nEpochs`: Number of epochs.
- `Loss`: Loss function.
- `AccMetrics`: Metrics.
- `ActFn`: Activation function.
- `Split`: Index of the split point and separates the data into the training and testing datasets.
- `Valid`: Validation set.

Details
Recurrent neural networks (RNNs) (Rumelhart 1986) add the explicit handling of order between observations when learning a mapping function from inputs to outputs. RNNs actually process single elements of any input sequence at a particular time, and maintain a 'state vector' in their hidden units. Nevertheless, when the interval of data dependencies increases, the standard RNNs tend to suffer increasingly heavily from the problem of either vanishing gradient or exploding gradient (Bengio et al. 1994; Lin et al. 1996).

Value
- `TrainFittedValue`: Training Fitted value for given time series data.
- `TestPredictedValue`: Final forecasted value of the RNN model.
- `fcast_criteria`: Different Forecasting evaluation criteria for RNN model.
References


See Also

LSTM, GRU

Examples

data("Data_Maize")
RNN_ts(Data_Maize)
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