Package ‘decompDL’

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Type Package

Title Decomposition Based Deep Learning Models for Time Series Forecasting

Version 0.1.0

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Description Hybrid model is the most promising forecasting method by combining decomposition and deep learning techniques to improve the accuracy of time series forecasting. Each decomposition technique decomposes a time series into a set of intrinsic mode functions (IMFs), and the obtained IMFs are modelled and forecasted separately using the deep learning models. Finally, the forecasts of all IMFs are combined to provide an ensemble output for the time series. The prediction ability of the developed models are calculated using international monthly price series of maize in terms of evaluation criteria like root mean squared error, mean absolute percentage error and, mean absolute error. For method details see Choudhary, K. et al. (2023). <https://ssca.org.in/media/14_SA44052022_R3_SA_21032023_Girish_Jha_FINAL_Finally.pdf>.

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`ceemdGRU` *Complementary Ensemble Empirical Mode Decomposition (CEEMD) Based Long Short Term (GRU) Model*

Description

The eemdGRU function computes forecasted value with different forecasting evaluation criteria for EEMD based GRU model.

Usage

```
ceemdGRU(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2,lg = 4,
LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`ensem.size`	Number of copies of the input signal to use as the ensemble.
`noise.st`	Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.

`lg`	Lag of time series data.
`LU`	Number of unit in GRU layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by CEEMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using GRU models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalCEEMDGRU_forecast`	Final forecasted value of the CEEMD based GRU model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_CEEMDGRU`	Mean Absolute Error (MAE) for CEEMD based GRU model.
`MAPE_CEEMDGRU`	Mean Absolute Percentage Error (MAPE) for CEEMD based GRU model.
`rmse_CEEMDGRU`	Root Mean Square Error (RMSE) for CEEMD based GRU model.
`AllIMF_plots`	Decomposed IMFs and residual plot.
`plot_testset`	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

eemdGRU

Examples

```
data("Data_Maize")
ceemdGRU(Data_Maize)
```

ceemdLSTM *Complementary Ensemble Empirical Mode Decomposition (CEEMD) Based Long Short Term (LSTM) Model*

Description

The eemdLSTM function computes forecasted value with different forecasting evaluation criteria for EEMD based LSTM model.

Usage

```
ceemdLSTM(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2,lg = 4,
LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`ensem.size`	Number of copies of the input signal to use as the ensemble.
`noise.st`	Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.
`lg`	Lag of time series data.
`LU`	Number of unit in GRU layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by CEEMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using LSTM models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.

`AllIMF_forecast`
: Forecasted value of all individual IMF.

`FinalCEEMDLSTM_forecast`
: Final forecasted value of the CEEMD based LSTM model. It is obtained by combining the forecasted value of all individual IMF.

`MAE_CEEMDLSTM`
: Mean Absolute Error (MAE) for CEEMD based LSTM model.

`MAPE_CEEMDLSTM`
: Mean Absolute Percentage Error (MAPE) for CEEMD based LSTM model.

`rmse_CEEMDLSTM`
: Root Mean Square Error (RMSE) for CEEMD based LSTM model.

`AllIMF_plots`
: Decomposed IMFs and residual plot.

`plot_testset`
: Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

eemdLSTM

Examples

```
data("Data_Maize")
ceemdLSTM(Data_Maize)
```

`ceemdRNN` *Complementary Ensemble Empirical Mode Decomposition (CEEMD) Based Long Short Term (RNN) Model*

Description

The eemdRNN function computes forecasted value with different forecasting evaluation criteria for EEMD based RNN model.

Usage

```
ceemdRNN(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2,lg = 4,
LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`ensem.size`	Number of copies of the input signal to use as the ensemble.
`noise.st`	Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.
`lg`	Lag of time series data.
`LU`	Number of unit in RNN layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by CEEMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using RNN models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalCEEMDRNN_forecast`	Final forecasted value of the CEEMD based RNN model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_CEEMDRNN`	Mean Absolute Error (MAE) for CEEMD based RNN model.
`MAPE_CEEMDRNN`	Mean Absolute Percentage Error (MAPE) for CEEMD based RNN model.
`rmse_CEEMDRNN`	Root Mean Square Error (RMSE) for CEEMD based RNN model.
`AllIMF_plots`	Decomposed IMFs and residual plot.
`plot_testset`	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

eemdRNN

Examples

```
data("Data_Maize")
ceemdRNN(Data_Maize)
```

Data_Maize — *Monthly International Maize Price Data*

Description

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

Usage

```
data("Data_Maize")
```

Format

A time series data with 126 observations.

`price` a time series

Details

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

Source

https://www.worldbank.org/en/research/commodity-markets

References

https://www.worldbank.org/en/research/commodity-markets

Examples

```
data(Data_Maize)
```

eemdGRU *Ensemble Empirical Mode Decomposition (EEMD) Based GRU Model*

Description

The eemdGRU function computes forecasted value with different forecasting evaluation criteria for EEMD based GRU model.

Usage

```
eemdGRU(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2,lg = 4,LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`ensem.size`	Number of copies of the input signal to use as the ensemble.
`noise.st`	Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.
`lg`	Lag of time series data.
`LU`	Number of unit in GRU layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by EEMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using GRU models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals. EEMD overcomes the limitation of the mode mixing and end effect problems of the empirical mode decomposition (EMD).

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.

`AllIMF_forecast`
: Forecasted value of all individual IMF.

`FinalEEMDGRU_forecast`
: Final forecasted value of the EEMD based GRU model. It is obtained by combining the forecasted value of all individual IMF.

`MAE_EEMDGRU` Mean Absolute Error (MAE) for EEMD based GRU model.

`MAPE_EEMDGRU` Mean Absolute Percentage Error (MAPE) for EEMD based GRU model.

`rmse_EEMDGRU` Root Mean Square Error (RMSE) for EEMD based GRU model.

`AllIMF_plots` Decomposed IMFs and residual plot.

`plot_testset` Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

emdGRU

Examples

```
data("Data_Maize")
eemdGRU(Data_Maize)
```

`eemdLSTM` *Ensemble Empirical Mode Decomposition (EEMD) Based Long Short Term (LSTM) Model*

Description

The eemdLSTM function computes forecasted value with different forecasting evaluation criteria for EEMD based LSTM model.

Usage

```
eemdLSTM(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2,lg = 4, LU = 2, Epochs = 2)
```

Arguments

- `data` — Input univariate time series (ts) data.
- `spl` — Index of the split point and separates the data into the training and testing datasets.
- `num.IMFs` — Number of Intrinsic Mode Function (IMF) for input series.
- `s.num` — Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
- `num.sift` — Number of siftings to find out IMFs.
- `ensem.size` — Number of copies of the input signal to use as the ensemble.
- `noise.st` — Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.
- `lg` — Lag of time series data.
- `LU` — Number of unit in GRU layer.
- `Epochs` — Number of epochs.

Details

A time series is decomposed by EEMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using LSTM models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals. EEMD overcomes the limitation of the mode mixing and end effect problems of the empirical mode decomposition (EMD).

Value

- `TotalIMF` — Total number of IMFs.
- `AllIMF` — List of all IMFs with residual for input series.
- `data_test` — Testing set used to measure the out of sample performance.
- `AllIMF_forecast` — Forecasted value of all individual IMF.
- `FinalEEMDLSTM_forecast` — Final forecasted value of the EEMD based LSTM model. It is obtained by combining the forecasted value of all individual IMF.
- `MAE_EEMDLSTM` — Mean Absolute Error (MAE) for EEMD based LSTM model.
- `MAPE_EEMDLSTM` — Mean Absolute Percentage Error (MAPE) for EEMD based LSTM model.
- `rmse_EEMDLSTM` — Root Mean Square Error (RMSE) for EEMD based LSTM model.
- `AllIMF_plots` — Decomposed IMFs and residual plot.
- `plot_testset` — Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

emdLSTM

Examples

```
data("Data_Maize")
eemdLSTM(Data_Maize)
```

---

eemdRNN *Ensemble Empirical Mode Decomposition (EEMD) Based RNN Model*

Description

The eemdRNN function computes forecasted value with different forecasting evaluation criteria for EEMD based RNN model.

Usage

```
eemdRNN(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2,lg = 4,
LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`ensem.size`	Number of copies of the input signal to use as the ensemble.
`noise.st`	Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.

`lg`	Lag of time series data.
`LU`	Number of unit in RNN layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by EEMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using RNN models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals. EEMD overcomes the limitation of the mode mixing and end effect problems of the empirical mode decomposition (EMD).

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalEEMDRNN_forecast`	Final forecasted value of the EEMD based RNN model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_EEMDRNN`	Mean Absolute Error (MAE) for EEMD based RNN model.
`MAPE_EEMDRNN`	Mean Absolute Percentage Error (MAPE) for EEMD based RNN model.
`rmse_EEMDRNN`	Root Mean Square Error (RMSE) for EEMD based RNN model.
`AllIMF_plots`	Decomposed IMFs and residual plot.
`plot_testset`	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

emdRNN

Examples

```
data("Data_Maize")
eemdRNN(Data_Maize)
```

emdGRU *Empirical Mode Decomposition (EMD) Based GRU Model*

Description

The emdGRU function computes forecasted value with different forecasting evaluation criteria for EMD based GRU model.

Usage

```
emdGRU(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L,lg = 4, LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`lg`	Lag of time series data.
`LU`	Number of unit in GRU layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by EMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using GRU models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalEMDGRU_forecast`	Final forecasted value of the EMD based GRU model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_EMDGRU`	Mean Absolute Error (MAE) for EMD based GRU model.

MAPE_EMDGRU	Mean Absolute Percentage Error (MAPE) for EMD based GRU model.
rmse_EMDGRU	Root Mean Square Error (RMSE) for EMD based GRU model.
AllIMF_plots	Decomposed IMFs and residual plot.
plot_testset	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q. and Liu, H.H. (1998) The empirical mode decomposition and the Hilbert spectrum for nonlinear and non stationary time series analysis. In Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences. 454, 903–995.

Jha, G.K. and Sinha, K. (2014) Time delay neural networks for time series prediction: An application to the monthly wholesale price of oilseeds in India. Neural Computing and Applications, 24, 563–571.

See Also

EMDGRU

Examples

```
data("Data_Maize")
emdGRU(Data_Maize)
```

---

emdLSTM *Empirical Mode Decomposition (EMD) Based Long Short Term (LSTM) Model*

Description

The emdLSTM function computes forecasted value with different forecasting evaluation criteria for EMD based LSTM model.

Usage

```
emdLSTM(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L,lg = 4, LU = 2, Epochs = 2)
```

Arguments

- `data` Input univariate time series (ts) data.
- `spl` Index of the split point and separates the data into the training and testing datasets.
- `num.IMFs` Number of Intrinsic Mode Function (IMF) for input series.
- `s.num` Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
- `num.sift` Number of siftings to find out IMFs.
- `lg` Lag of time series data.
- `LU` Number of unit in LSTM layer.
- `Epochs` Number of epochs.

Details

A time series is decomposed by EMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using LSTM models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals.

Value

- `TotalIMF` Total number of IMFs.
- `AllIMF` List of all IMFs with residual for input series.
- `data_test` Testing set used to measure the out of sample performance.
- `AllIMF_forecast` Forecasted value of all individual IMF.
- `FinalEMDLSTM_forecast` Final forecasted value of the EMD based LSTM model. It is obtained by combining the forecasted value of all individual IMF.
- `MAE_EMDLSTM` Mean Absolute Error (MAE) for EMD based LSTM model.
- `MAPE_EMDLSTM` Mean Absolute Percentage Error (MAPE) for EMD based LSTM model.
- `rmse_EMDLSTM` Root Mean Square Error (RMSE) for EMD based LSTM model.
- `AllIMF_plots` Decomposed IMFs and residual plot.
- `plot_testset` Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q. and Liu, H.H. (1998) The empirical mode decomposition and the Hilbert spectrum for nonlinear and non stationary time series analysis. In Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences. 454, 903–995.

Jha, G.K. and Sinha, K. (2014) Time delay neural networks for time series prediction: An application to the monthly wholesale price of oilseeds in India. Neural Computing and Applications, 24, 563–571.

See Also

EMDLSTM

Examples

```
data("Data_Maize")
emdLSTM(Data_Maize)
```

`emdRNN` *Empirical Mode Decomposition (EMD) Based RNN Model*

Description

The emdRNN function computes forecasted value with different forecasting evaluation criteria for EMD based RNN model.

Usage

```
emdRNN(data, spl=0.8, num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L,lg = 4, LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	Index of the split point and separates the data into the training and testing datasets.
`num.IMFs`	Number of Intrinsic Mode Function (IMF) for input series.
`s.num`	Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
`num.sift`	Number of siftings to find out IMFs.
`lg`	Lag of time series data.
`LU`	Number of unit in RNN layer.
`Epochs`	Number of epochs.

Details

A time series is decomposed by EMD into a set of intrinsic mode functions (IMFs) and a residual, which are modelled and predicted independently using RNN models. Finally, the ensemble output for the price series is produced by combining the forecasts of all IMFs and residuals.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalEMDRNN_forecast`	Final forecasted value of the EMD based RNN model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_EMDRNN`	Mean Absolute Error (MAE) for EMD based RNN model.
`MAPE_EMDRNN`	Mean Absolute Percentage Error (MAPE) for EMD based RNN model.
`rmse_EMDRNN`	Root Mean Square Error (RMSE) for EMD based RNN model.
`AllIMF_plots`	Decomposed IMFs and residual plot.
`plot_testset`	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

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Jha, G.K. and Sinha, K. (2014) Time delay neural networks for time series prediction: An application to the monthly wholesale price of oilseeds in India. Neural Computing and Applications, 24, 563–571.

See Also

EMDRNN

Examples

```
data("Data_Maize")
emdRNN(Data_Maize)
```

`vmdGRU` *Variational Mode Decomposition Based GRU Model*

Description

This function computes forecasted value with different forecasting evaluation criteria for Variational Mode Decomposition (VMD) Based GRU Model.

Usage

```
vmdGRU (data, spl=0.8, n=4, alpha=2000, tau=0, D=FALSE, LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	The forecast horizon.
`n`	The number of IMFs.
`alpha`	The balancing parameter.
`tau`	Time-step of the dual ascent.
`D`	a boolean.
`LU`	Number of unit in GRU layer.
`Epochs`	Number of epochs.

Details

The Variational Mode Decomposition method is a novel adaptive, non-recursive signal decomposition technology, which was introduced by Dragomiretskiy and Zosso (2014). VMD method helps to solve current decomposition methods limitation such as lacking mathematical theory, recursive sifting process which not allows for backward error correction, hard-band limits, the requirement to predetermine filter bank boundaries, and sensitivity to noise. It decomposes a series into sets of IMFs. GRU used to forecast decomposed components individually . Finally, the prediction results of all components are aggregated to formulate an ensemble output for the input time series.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalVMDGRU_forecast`	Final forecasted value of the VMD based GRU model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_VMDGRU`	Mean Absolute Error (MAE) for VMD based GRU model.

MAPE_VMDGRU	Mean Absolute Percentage Error (MAPE) for VMD based GRU model.
rmse_VMDGRU	Root Mean Square Error (RMSE) for VMD based GRU model.
AllIMF_plots	Decomposed IMFs and residual plot.
plot_testset	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

emdGRU

Examples

```
data("Data_Maize")
vmdGRU(Data_Maize)
```

---

vmdLSTM *Variational Mode Decomposition Based LSTM Model*

Description

This function computes forecasted value with different forecasting evaluation criteria for Variational Mode Decomposition (VMD) Based LSTM Model.

Usage

```
vmdLSTM (data, spl=0.8, n=4, alpha=2000, tau=0, D=FALSE, LU = 2, Epochs = 2)
```

Arguments

data	Input univariate time series (ts) data.
spl	The forecast horizon.
n	The number of IMFs.
alpha	The balancing parameter.
tau	Time-step of the dual ascent.
D	a boolean.
LU	Number of unit in GRU layer.
Epochs	Number of epochs.

Details

The Variational Mode Decomposition method is a novel adaptive, non-recursive signal decomposition technology, which was introduced by Dragomiretskiy and Zosso (2014). VMD method helps to solve current decomposition methods limitation such as lacking mathematical theory, recursive sifting process which not allows for backward error correction, hard-band limits, the requirement to predetermine filter bank boundaries, and sensitivity to noise. It decomposes a series into sets of IMFs. LSTM used to forecast decomposed components individually . Finally, the prediction results of all components are aggregated to formulate an ensemble output for the input time series.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalVMDLSTM_forecast`	Final forecasted value of the VMD based LSTM model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_VMDLSTM`	Mean Absolute Error (MAE) for VMD based LSTM model.
`MAPE_VMDLSTM`	Mean Absolute Percentage Error (MAPE) for VMD based LSTM model.
`rmse_VMDLSTM`	Root Mean Square Error (RMSE) for VMD based LSTM model.
`AllIMF_plots`	Decomposed IMFs and residual plot.
`plot_testset`	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

emdLSTM

Examples

```
data("Data_Maize")
vmdLSTM(Data_Maize)
```

vmdRNN — *Variational Mode Decomposition Based RNN Model*

Description

This function computes forecasted value with different forecasting evaluation criteria for Variational Mode Decomposition (VMD) Based RNN Model.

Usage

```
vmdRNN (data, spl=0.8, n=4, alpha=2000, tau=0, D=FALSE, LU = 2, Epochs = 2)
```

Arguments

`data`	Input univariate time series (ts) data.
`spl`	The forecast horizon.
`n`	The number of IMFs.
`alpha`	The balancing parameter.
`tau`	Time-step of the dual ascent.
`D`	a boolean.
`LU`	Number of unit in RNN layer.
`Epochs`	Number of epochs.

Details

The Variational Mode Decomposition method is a novel adaptive, non-recursive signal decomposition technology, which was introduced by Dragomiretskiy and Zosso (2014). VMD method helps to solve current decomposition methods limitation such as lacking mathematical theory, recursive sifting process which not allows for backward error correction, hard-band limits, the requirement to predetermine filter bank boundaries, and sensitivity to noise. It decomposes a series into sets of IMFs. RNN used to forecast decomposed components individually . Finally, the prediction results of all components are aggregated to formulate an ensemble output for the input time series.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF.
`FinalVMDRNN_forecast`	Final forecasted value of the VMD based RNN model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_VMDRNN`	Mean Absolute Error (MAE) for VMD based RNN model.

MAPE_VMDRNN	Mean Absolute Percentage Error (MAPE) for VMD based RNN model.
rmse_VMDRNN	Root Mean Square Error (RMSE) for VMD based RNN model.
AllIMF_plots	Decomposed IMFs and residual plot.
plot_testset	Test set forecasted vs actual value plot.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble empirical mode decomposition: A case study of daily potato price series. Indian journal of agricultural sciences, 89(5), 882–886.

Wu, Z. and Huang, N.E. (2009) Ensemble empirical mode decomposition: a noise assisted data analysis method. Advances in adaptive data analysis, 1(1), 1–41.

See Also

emdRNN

Examples

```
data("Data_Maize")
vmdRNN(Data_Maize)
```

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