Package 'EEMDelm'

January 20, 2025

Type Package

Title Ensemble Empirical Mode Decomposition and Its Variant Based ELM Model

Version 0.1.1

Maintainer Girish Kumar Jha <girish.stat@gmail.com>

Description Forecasting univariate time series with different decomposition based Extreme Learning Machine models. For method details see Yu L, Wang S, Lai KK (2008). <doi:10.1016/j.eneco.2008.05.003>, Parida M, Behera MK, Nayak N (2018). <doi:10.1109/ICSESP.2018.8376723>.

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Encoding UTF-8

LazyData true

RoxygenNote 7.2.1

Imports forecast, nnfor, Rlibeemd

Depends R (>= 2.10)

NeedsCompilation no

Author Girish Kumar Jha [aut, cre],
Kapil Choudhary [aut, ctb],
Rajeev Ranjan Kumar [ctb],
Ronit Jaiswal [ctb]

Repository CRAN

Date/Publication 2022-08-09 06:50:02 UTC

Contents

CEEMDANelm	*Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise Based ELM Model*

Description

The CEEMDANelm function computes forecasted value with different forecasting evaluation criteria for Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise based Extreme Learning Machine model.

Usage

```
CEEMDANelm(data, stepahead=10,
num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2)
```

Arguments

data	Input univariate time series (ts) data.
stepahead	The forecast horizon.
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.

Details

Some useless IMFs are generated in EMD and EEMD, which degrades performance of these algorithms. Therefore, reducing the number of these useless IMFs is advantageous for improving the computation efficiency of these techniques, Torres et al.(2011) proposed CEEMDAN. Fewer IMFs may be generated on the premise of successfully separating different components of a series by using this algorithm, which can reduce the computational cost.

Value

TotalIMF	Total number of IMFs.
AllIMF	List of all IMFs with residual for input series.
data_test	Testing set is used to measure the out of sample performance.
AllIMF_forecast	
	Forecasted value of all individual IMF

FinalCEEMDANELM_forecast

> Final forecasted value of the CEEMDANELM model.It is obtained by combining the forecasted value of all individual IMF.

MAE_CEEMDANELM Mean Absolute Error (MAE) for CEEMDANELM model.

MAPE_CEEMDANELM

> Mean Absolute Percentage Error (MAPE) for CEEMDANELM model.

rmse_CEEMDANELM

> Root Mean Square Error (RMSE) for CEEMDANELM model.

References

Huang, G.B., Zhu, Q.Y. and Siew, C.K. (2006). Extreme learning machine: theory and applications. Neurocomputing, 70, 489–501.

Torres, M.E., Colominas, M.A., Schlotthauer, G. and Flandrin, P. (2011) A complete ensemble empirical mode decomposition with adaptive noise. In 2011 IEEE international conference on acoustics, speech and signal processing (ICASSP) (pp. 4144–4147). IEEE.

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

EMDelm, EEMDELM

Examples

```
data("Data_Soybean")
CEEMDANelm(Data_Soybean)
```

Data_Soybean *Monthly International Soybean Oil Price*

Description

Monthly international Soyabean oil price from August 2001 to June 2020.

Usage

```
data("Data_Soybean")
```

Format

A time series data with 227 observations.

price a time series

Details

Dataset contains 227 observations of monthly international Soyabean oil price. 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_Soybean)
```

EEMDELM   *Ensemble Empirical Mode Decomposition Based ELM Model*

Description

The EEMDelm function computes forecasted value with different forecasting evaluation criteria for Ensemble Empirical Mode Decomposition based Extreme Learning Machine model.

Usage

```
EEMDELM(data, stepahead=10,
num.IMFs=emd_num_imfs(length(data)), s.num=4L,
num.sift=50L, ensem.size=250L, noise.st=0.2)
```

Arguments

data	Input univariate time series (ts) data.
stepahead	The forecast horizon.
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.

Details

To overcome the problem of EMD (i.e. mode mixing), Ensemble Empirical Mode Decomposition (EEMD) method was developed by Wu and Huang (2009), which significantly reduces the chance of mode mixing and represents a substantial improvement over the original EMD.

Value

`TotalIMF`	Total number of IMFs.
`AllIMF`	List of all IMFs with residual for input series.
`data_test`	Testing set is used to measure the out of sample performance.
`AllIMF_forecast`	
	Forecasted value of all individual IMF.
`FinalEEMDELM_forecast`	
	Final forecasted value of the EEMDELM model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_EEMDELM`	Mean Absolute Error (MAE) for EEMDELM model.
`MAPE_EEMDELM`	Mean Absolute Percentage Error (MAPE) for EEMDELM model.
`rmse_EEMDELM`	Root Mean Square Error (RMSE) for EEMDELM model.

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.

Huang, G.B., Zhu, Q.Y. and Siew, C.K. (2006) Extreme learning machine: theory and applications. Neurocomputing, 70, 489–501.

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

EMDelm, CEEMDANelm

Examples

```
data("Data_Soybean")
EEMDELM(Data_Soybean)
```

EMDelm   *Empirical Mode Decomposition Based ELM Model*

Description

The EMDelm function computes forecasted value with different forecasting evaluation criteria for Empirical Mode Decomposition based Extreme Learning Machine model.

Usage

```
EMDelm(xt, stepahead = 10, s.num = 4L, num.sift = 50L)
```

Arguments

xt	Input univariate time series (ts) data.
stepahead	The forecast horizon.
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.

Details

This function decomposes the original time series into several independent intrinsic mode functions (IMFs) and one residual component (Huang et al., 1998). Then extreme learning machine, a class of feedforward neural network is used to forecast these IMFs and residual component individually (Huang et al., 2006). Finally, the prediction results of all IMFs including residual are aggregated to formulate an ensemble output for the original time series.

Value

TotalIMF	Total number of IMFs.
AllIMF	List of all IMFs with residual for input series.
data_test	Testing set is used to measure the out of sample performance.
AllIMF_forecast	
	Forecasted value of all individual IMF.
FinalEMDELM_forecast	
	Final forecasted value of the EMDELM model.It is obtained by combining the forecasted value of all individual IMF.
MAE_EMDELM	Mean Absolute Error (MAE) for EMDELM model.
MAPE_EMDELM	Mean Absolute Percentage Error (MAPE) for EMDELM model.
rmse_EMDELM	Root Mean Square Error (RMSE) for EMDELM model.

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.

Dong, J., Dai, W., Tang, L. and Yu, L. (2019) Why do EMD based methods improve prediction. A multiscale complexity perspective. Journal of Forecasting, 38(7), 714–731.

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.

Huang, G.B., Zhu, Q.Y. and Siew, C.K. (2006). Extreme learning machine: theory and applications. Neurocomputing, 70, 489–501.

See Also

EEMDELM, CEEMDANelm

Examples

```
data("Data_Soybean")
EMDelm(Data_Soybean)
```

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