Package ‘eemdTDNN’

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Title EEMD and Its Variant Based Time Delay Neural Network Model

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License GPL-3

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ceemdanTDNN *CEEMDAN Based Time Delay Neural Network Model*

Description

The ceemdanTDNN function computes forecasted value for Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise Based Time Delay Neural Network Model with different forecasting evaluation criteria.

Usage

```
ceemdanTDNN(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

Torres et al.(2011) proposed Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). This algorithm generates a Fewer IMFs on the premise of successfully separating different components of a series, 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 used to measure the out of sample performance.
`AllIMF_forecast`	Forecasted value of all individual IMF
`FinalCEEMDANTDNN_forecast`	Final forecasted value of the CEEMDAN based TDNN model. It is obtained by combining the forecasted value of all individual IMF.

`MAE_CEEMDANTDNN`
: Mean Absolute Error (MAE) for CEEMDAN based TDNN model.

`MAPE_CEEMDANTDNN`
: Mean Absolute Percentage Error (MAPE) for CEEMDAN based TDNN model.

`rmse_CEEMDANTDNN`
: Root Mean Square Error (RMSE) for CEEMDAN based TDNN model.

References

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

emdTDNN, EEMDTDNN

Examples

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

`Data_Maize` *Monthly International Maize Price Data*

Description

Monthly international Maize price (Dollor per million ton) from January 2001 to December 2019.

Usage

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

Format

A time series data with 228 observations.

`price` a time series

Details

Dataset contains 228 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)
```

EEMDTDNN — *Ensemble Empirical Mode Decomposition Based Time Delay Neural Network Model*

Description

The EEMDTDNN function computes forecasted value with different forecasting evaluation criteria for Ensemble Empirical Mode Decomposition based Time Delay Neural Network Model.

Usage

```
EEMDTDNN(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 mode mixing in EMD decomposition technique, Ensemble Empirical Mode Decomposition (EEMD) method was developed by Wu and Huang (2009). EEMD 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 used to measure the out of sample performance.
AllIMF_forecast	Forecasted value of all individual IMF.
FinalEEMDTDNN_forecast	Final forecasted value of the EEMD based TDNN model. It is obtained by combining the forecasted value of all individual IMF.
MAE_EEMDTDNN	Mean Absolute Error (MAE) for EEMD based TDNN model.
MAPE_EEMDTDNN	Mean Absolute Percentage Error (MAPE) for EEMD based TDNN model.
rmse_EEMDTDNN	Root Mean Square Error (RMSE) for EEMD based TDNN 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.

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

emdTDNN, ceendanTDNN

Examples

```
Data("Data_Maize")
EEMDTDNN(Data_Maize)
```

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emdTDNN — *Empirical Mode Decomposition Based Time Delay Neural Network Model*

Description

The emdTDNN function gives forecasted value of Empirical Mode Decomposition based Time Delay Neural Network Model with different forecasting evaluation criteria.

Usage

```
emdTDNN(data, stepahead=10,
num.IMFs=emd_num_imfs(length(data)),
s.num=4L, num.sift=50L)
```

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.

Details

This function firstly, decompose the nonlinear and nonstationary time series into several independent intrinsic mode functions (IMFs) and one residual component (Huang et al., 1998). Secondly, time delay neural network is used to forecast these IMFs and residual component individually. Finally, the prediction results of all IMFs including residual are aggregated to form the final forecasted value for given 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.
FinalEMDTDNN_forecast	Final forecasted value of the EMD based TDNN model. It is obtained by combining the forecasted value of all individual IMF.
MAE_EMDTDNN	Mean Absolute Error (MAE) for EMD based TDNN model.
MAPE_EMDTDNN	Mean Absolute Percentage Error (MAPE) for EMD based TDNN model.
rmse_EMDTDNN	Root Mean Square Error (RMSE) for EMD based TDNN 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.

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

EEMDTDNN, ceemdanTDNN

Examples

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

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