Package ‘decompML’

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Type Package

Title Decomposition Based Machine Learning Model

Version 0.1.1

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Description The hybrid model is a highly effective forecasting approach that integrates decomposition techniques with machine learning to enhance time series prediction accuracy. Each decomposition technique breaks down a time series into multiple intrinsic mode functions (IMFs), which are then individually modeled and forecasted using machine learning algorithms. The final forecast is obtained by aggregating the predictions of all IMFs, producing an ensemble output for the time series. The performance of the developed models is evaluated using international monthly maize price data, assessed through metrics such as root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE). For method details see Choudhary, K. et al. (2023). <https://ssca.org.in/media/14_SA44052022_R3_SA_21032023_Girish_Jha_FINAL_Finally.pdf>.

License GPL-3

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Contents

`ceemdanARIMA` *CEEMDAN Based Auto Regressive Integrated Moving Average Model*

Description

The ceemdanARIMA function gives forecasted value of CEEMDAN based Auto Regressive Integrated Moving Average Model with different forecasting evaluation criteria.

Usage

```
ceemdanARIMA(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 ceemdan 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

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, Auto Regressive Integrated Moving Average 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.
- `FinalceemdanARIMA_forecast` Final forecasted value of the ceemdan based ARIMA model. It is obtained by combining the forecasted value of all individual IMF.
- `MAE_ceemdanARIMA` Mean Absolute Error (MAE) for ceemdan based ARIMA model.
- `MAPE_ceemdanARIMA` Mean Absolute Percentage Error (MAPE) for ceemdan based ARIMA model.
- `rmse_ceemdanARIMA` Root Mean Square Error (RMSE) for ceemdan based ARIMA model.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble CEEMDAN: 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 CEEMDAN 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) Auto Regressive Integrated Moving Averages for time series prediction: An application to the monthly wholesale price of oilseeds in India. Neural Computing and Applications, 24, 563–571.

See Also

eemdARIMA, emdARIMA

Examples

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

`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_Maize")
ceemdanELM(Data_Maize)
```

---

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*

Description

Monthly international Maize price from Janurary 2001 to December 2021.

Usage

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

Format

A time series data with 252 observations.

`price` a time series

Details

Dataset contains 252 observations of monthly international Maize 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_Maize)
```

eemdARIMA — *Ensemble Empirical Mode Decomposition Based Auto Regressive Integrated Moving Average Model*

Description

The eemdARIMA function gives forecasted value of Ensemble Empirical Mode Decomposition based Auto Regressive Integrated Moving Average Model with different forecasting evaluation criteria.

Usage

```
eemdARIMA(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 eemd 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

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, Auto Regressive Integrated Moving Average 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.

FinaleemdARIMA_forecast
: Final forecasted value of the eemd based ARIMA model. It is obtained by combining the forecasted value of all individual IMF.

MAE_eemdARIMA
: Mean Absolute Error (MAE) for eemd based ARIMA model.

MAPE_eemdARIMA
: Mean Absolute Percentage Error (MAPE) for eemd based ARIMA model.

rmse_eemdARIMA
: Root Mean Square Error (RMSE) for eemd based ARIMA model.

References

Choudhary, K., Jha, G.K., Kumar, R.R. and Mishra, D.C. (2019) Agricultural commodity price analysis using ensemble 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 Ensemble 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) Auto Regressive Integrated Moving Averages for time series prediction: An application to the monthly wholesale price of oilseeds in India. Neural Computing and Applications, 24, 563–571.

See Also

eemdARIMA, ceeemdanARIMA

Examples

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

---

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_Maize")
eemdELM(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)
```

---

emdARIMA *Empirical Mode Decomposition Based Auto Regressive Integrated Moving Average Model*

Description

The emdARIMA function gives forecasted value of Empirical Mode Decomposition based Auto Regressive Integrated Moving Average Model with different forecasting evaluation criteria.

Usage

```
emdARIMA(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, Auto Regressive Integrated Moving Average 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.
FinalEMDARIMA_forecast	Final forecasted value of the EMD based ARIMA model. It is obtained by combining the forecasted value of all individual IMF.
MAE_EMDARIMA	Mean Absolute Error (MAE) for EMD based ARIMA model.
MAPE_EMDARIMA	Mean Absolute Percentage Error (MAPE) for EMD based ARIMA model.
rmse_EMDARIMA	Root Mean Square Error (RMSE) for EMD based ARIMA 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) Auto Regressive Integrated Moving Averages for time series prediction: An application to the monthly wholesale price of oilseeds in India. Neural Computing and Applications, 24, 563–571.

See Also

eemdARIMA, ceemdanARIMA

Examples

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

---

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

emdELM, ceemdanelm

Examples

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

`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)
```

`vmdARIMA` *Variational Mode Decomposition Based Autoregressive Integrated Moving Average Model*

Description

The vmdARIMA function computes forecasted value with different forecasting evaluation criteria for Variational Mode Decomposition (VMD) Based Autoregressive Integrated Moving Average (ARIMA).

Usage

```
vmdARIMA (data, stepahead=10, nIMF=4, alpha=2000, tau=0, D=FALSE)
```

Arguments

`data`	Input univariate time series (ts) data.
`stepahead`	The forecast horizon.
`nIMF`	The number of IMFs.
`alpha`	The balancing parameter.
`tau`	Time-step of the dual ascent.
`D`	a boolean.

Details

In this function, the variational mode decomposition (VMD) used for mining the trend features and detailed features contained in a time series. Moreover, the corresponding autoregressive integrated moving average (ARIMA) models were derived to reflect the different features of the IMFs. The final forecasted values obtained for a given time series.

Value

`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

`FinalvmdARIMA_forecast` Final forecasted value of the VMD based ARIMA model. It is obtained by combining the forecasted value of all individual IMF.

`MAE_vmdARIMA` Mean Absolute Error (MAE) for vmdARIMA model.

`MAPE_vmdARIMA` Mean Absolute Percentage Error (MAPE) for vmdARIMA model.

`rmse_vmdARIMA` Root Mean Square Error (RMSE) for vmdARIMA model.

References

Box, G. E., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley and Sons.

Dragomiretskiy, K.and Zosso, D. (2014). Variational mode decomposition. IEEE transactions on signal processing, 62(3), 531–544.

Wang, H., Huang, J., Zhou, H., Zhao, L. and Yuan, Y. (2019). An integrated variational mode decomposition and arima model to forecast air temperature. Sustainability, 11(15), 4018.

See Also

vmdTDNN,vmdELM

Examples

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

---

vmdELM *Variational Mode Decomposition Based Extreme Learning Machine Model*

Description

The vmdELM function computes forecasted value with different forecasting evaluation criteria for Variational Mode Decomposition (VMD) Based Extreme learning machine (ELM).

Usage

```
vmdELM (data, stepahead=10, nIMF=4, alpha=2000, tau=0, D=FALSE)
```

Arguments

data	Input univariate time series (ts) data.
stepahead	The forecast horizon.
nIMF	The number of IMFs.
alpha	The balancing parameter.
tau	Time-step of the dual ascent.
D	a boolean.

Details

This function decomposes a nonlinear, nonstationary time series into different IMFs using VMD (Qian et al., 2019). Extreme learning machine (ELM) is used to forecast decomposed IMFs individually. Finally, the prediction results of all three components are aggregated to formulate an ensemble output for the input time series.

Value

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
FinalvmdELM_forecast	Final forecasted value of the VMD based ELM model. It is obtained by combining the forecasted value of all individual IMF.
MAE_vmdELM	Mean Absolute Error (MAE) for vmdELM model.
MAPE_vmdELM	Mean Absolute Percentage Error (MAPE) for vmdELM model.
rmse_vmdELM	Root Mean Square Error (RMSE) for vmdELM model.

References

Dragomiretskiy, K.and Zosso, D. (2014). Variational mode decomposition. IEEE transactions on signal processing, 62(3), 531–544.

Shao, Z., Chao, F., Yang, S. L., & Zhou, K. L. (2017). A review of the decomposition methodology for extracting and identifying the fluctuation characteristics in electricity demand forecasting. Renewable and Sustainable Energy Reviews, 75, 123–136.

Qian, Z., Pei, Y., Zareipour, H. andChen, N. (2019). A review and discussion of decomposition-based hybrid models for wind energy forecasting applications. Applied energy, 235, 939–953.

See Also

vmdTDNN,vmdARIMA

Examples

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

`vmdTDNN` *Variational Mode Decomposition Based Time Delay Neural Network Model*

Description

The vmdTDNN function computes forecasted value with different forecasting evaluation criteria for Variational Mode Decomposition (VMD) Based Time Delay Neural Network Model (TDNN).

Usage

```
vmdTDNN (data, stepahead=10, nIMF=4, alpha=2000, tau=0,D=FALSE)
```

Arguments

`data`	Input univariate time series (ts) data.
`stepahead`	The forecast horizon.
`nIMF`	The number of IMFs.
`alpha`	The balancing parameter.
`tau`	Time-step of the dual ascent.
`D`	a boolean.

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. Time-delay neural networks are used to forecast decomposed components individually (Jha and Sinha, 2014). Finally, the prediction results of all components are aggregated to formulate an ensemble output for the input time series.

Value

`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
`FinalvmdTDNN_forecast`	Final forecasted value of the VMD based TDNN model. It is obtained by combining the forecasted value of all individual IMF.
`MAE_vmdTDNN`	Mean Absolute Error (MAE) for vmdTDNN model.
`MAPE_vmdTDNN`	Mean Absolute Percentage Error (MAPE) for vmdTDNN model.
`rmse_vmdTDNN`	Root Mean Square Error (RMSE) for vmdTDNN model.

References

Choudhury, K., Jha, G. K., Das, P. and Chaturvedi, K. K. (2019). Forecasting potato price using ensemble artificial neural networks. Indian Journal of Extension Education, 55(1), 73–77.

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.

Dragomiretskiy, K.and Zosso, D. (2014). Variational mode decomposition. IEEE transactions on signal processing, 62(3), 531–544.

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(3–4), 563–571.

See Also

vmdARIMA,vmdELM

Examples

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

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