Package 'vmdTDNN'

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Type Package

Title VMD Based Time Delay Neural Network Model

Version 0.1.1

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Description Forecasting univariate time series with Variational Mode Decomposition (VMD) based time delay neural network models.For method details see Konstantin, D.and Dominique, Z. (2014). <doi:10.1109/TSP.2013.2288675>.

License GPL-3

Encoding UTF-8

LazyData true

RoxygenNote 7.1.2

Imports forecast, nnfor, VMDecomp

Depends R (>= 2.10)

Suggests testthat (>= 3.0.0)

Config/testthat/edition 3

NeedsCompilation no

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R topics documented:

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)
```

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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