Package ‘decompDL’

December 4, 2023

Type Package

Title Decomposition Based Deep Learning Models for Time Series Forecasting

Version 0.1.0

Maintainer Kapil Choudhary <kapiliasri@gmail.com>

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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Encoding UTF-8

LazyData true

RoxygenNote 7.2.3

Imports keras, tensorflow, reticulate, tsutils, stats, BiocGenerics, utils, graphics, magrittr, Rlibeemd, TSdeeplearning, VMDecomp

Depends R (>= 2.10)

NeedsCompilation no

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Repository CRAN

Date/Publication 2023-12-04 16:50:02 UTC
The `ceemdGRU` function computes forecasted value with different forecasting evaluation criteria for EEMD based GRU model.

**Usage**

```r
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.
ceemdGRU

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


See Also
eemdGRU

Examples

data("Data_Maize")
ceemdGRU(Data_Maize)
Description

The `ceemdLSTM` 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


See Also
eemdLSTM

Examples

data("Data_Maize")
ceemdLSTM(Data_Maize)
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


Data_Maize

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

References

Examples

data(Data_Maize)
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


See Also
eemdGRU

Examples

data("Data_Maize")
eemdGRU(Data_Maize)

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

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>data</td>
<td>Input univariate time series (ts) data.</td>
</tr>
<tr>
<td>spl</td>
<td>Index of the split point and separates the data into the training and testing datasets.</td>
</tr>
<tr>
<td>num.IMFs</td>
<td>Number of Intrinsic Mode Function (IMF) for input series.</td>
</tr>
<tr>
<td>s.num</td>
<td>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.</td>
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<td>num.sift</td>
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<tr>
<td>noise.st</td>
<td>Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.</td>
</tr>
<tr>
<td>lg</td>
<td>Lag of time series data.</td>
</tr>
<tr>
<td>LU</td>
<td>Number of unit in GRU layer.</td>
</tr>
<tr>
<td>Epochs</td>
<td>Number of epochs.</td>
</tr>
</tbody>
</table>

### 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

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


## See Also

emdLSTM

## Examples

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

## Description

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

## Usage

```r
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

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>data</code></td>
<td>Input univariate time series (ts) data.</td>
</tr>
<tr>
<td><code>spl</code></td>
<td>Index of the split point and separates the data into the training and testing datasets.</td>
</tr>
<tr>
<td><code>num.IMFs</code></td>
<td>Number of Intrinsic Mode Function (IMF) for input series.</td>
</tr>
<tr>
<td><code>s.num</code></td>
<td>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.</td>
</tr>
<tr>
<td><code>num.sift</code></td>
<td>Number of siftings to find out IMFs.</td>
</tr>
<tr>
<td><code>ensem.size</code></td>
<td>Number of copies of the input signal to use as the ensemble.</td>
</tr>
<tr>
<td><code>noise.st</code></td>
<td>Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.</td>
</tr>
</tbody>
</table>
1g  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

See Also
eemdRNN

Examples
data("Data_Maize")
eemdRNN(Data_Maize)
**Description**

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

**Usage**

```r
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.
EMDGRU

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)

References


See Also

EMDGRU

Examples

data("Data_Maize")
emdGRU(Data_Maize)
**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**


See Also

EMDLSTM

Examples

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

Description

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

Usage

```r
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.
emdRNN

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


See Also

EMDRNN

Examples

data(“Data_Maize”)
emdRNN(Data_Maize)
**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**

\[ \text{vmdGRU} \left( \text{data}, \text{spl}=0.8, \text{n}=4, \text{alpha}=2000, \text{tau}=0, \text{D}=\text{FALSE}, \text{LU}=2, \text{Epochs}=2 \right) \]

**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.
vmdLSTM

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


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


See Also

emdLSTM

Examples

data("Data_Maize")
vmdLSTM(Data_Maize)
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


See Also

emdRNN

Examples

data("Data_Maize")
vmdRNN(Data_Maize)
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