Method Description

General Information

Type of Entry (*Academic, Practitioner, Researcher, Student*)	**Student**
First Name	**Kasun**
Last Name	**Bandara**
Country	**Australia**
Type of Affiliation (*University, Company-Organization, Individual*)	**University**
Affiliation	**Monash University**

Team Members (*if applicable*):

1st Member	
First Name	Christoph
Last Name	Bergmeir
Country	Australia
Affiliation	Monash University
2nd Member	
First Name	Hansika
Last Name	Hewamalage
Country	Australia
Affiliation	Monash University

Information about the method utilized

Name of Method	**ResidualLSTM**
Type of Method (*Statistical, Machine Learning, Combination, Other*)	**Combination**
Short Description (up to 200 words)	***Please check the description**

Extended Description:

<u>Yearly time series</u>

I. Log transforming the time series : log(ts)
II. Applying ETS () [1] on the log transformed time series for the initial forecasts (F1). (setting frequency as 1)
III. Applying LSTM algorithm to each type (i.e. Demographic, Finance etc.) separately as different models, according to [2] (**excluding** the log transformation and STL decomposition) on the residuals generated by (ii) method. (F2)
IV. Adding the residual forecasts to the base forecasts (F1 + F2) to generate the final forecasts.
V. Forecasts that are negative after the addition (F1 + F2) are replaced with Zeros.

Please note that the final forecasts are back transformed using the exponential function exp()

Quarterly time series

I. Applying ETS () [1] on the time series for the initial forecasts (F1). (setting frequency as 4)
II. If previous step (i) generates negative forecasts, then use ETS (λ=0) on the corresponding series again (F1)
III. Applying LSTM algorithm to each type (i.e. Demographic, Finance etc.) separately as different models, according to [2] (**excluding** the log transformation and STL decomposition) on the residuals generated by (i) method. (F2)
IV. Adding the residual forecasts to the base forecasts (F1 + F2) to generate the final forecasts.
V. Forecasts that are negative after the addition (F1 + F2) are replaced with Zeros.

Monthly time series

I. Applying ETS () [1] on time series for the initial forecasts (F1). (setting frequency as 12)
II. If previous step (i) generates negative forecasts, then use ETS (λ=0) on the corresponding series again (F1)
III. Applying LSTM algorithm to each type (i.e. Demographic, Finance etc.) separately as different models, according to [2] (**excluding** the log transformation and STL decomposition) on the residuals generated by (ii) method. (F2)
IV. Adding the residual forecasts to the base forecasts (F1 + F2) to generate the final forecasts.
V. Forecasts that are negative after the addition (F1 + F2) are replaced with Zeros.

Weekly time series

I. Log transforming the time series : log(ts)
II. Applying TBATS() [3] on the log transformed time series for the initial forecasts (F1). (setting seasonal.periods=c(52))
III. Applying LSTM algorithm to each type (i.e. Demographic, Finance etc.) separately as different models, according to [2] (**excluding** the log transformation and STL decomposition) on the residuals generated by (ii) method. (F2)
IV. Adding the residual forecasts to the base forecasts (F1 + F2) to generate the final forecasts.
V. Forecasts that are negative after the addition (F1 + F2) are replaced with Zeros.

Please note that the final forecasts are back transformed using the exponential function exp()

Daily time series

I. Applying TBATS() [3] on the log transformed time series for the initial forecasts (F1). (setting seasonal.periods=c(7,365.25))
II. If previous step (i) generates negative forecasts, then use ETS (λ=0) on the corresponding series again (F1)
III. Applying LSTM algorithm to each type (i.e. Demographic, Finance etc.) separately as different models, according to [2] (**excluding** the log transformation and STL decomposition) on the residuals generated by (i) method. (F2)
IV. Adding the residual forecasts to the base forecasts (F1 + F2) to generate the final forecasts.
V. Forecasts that are negative after the addition (F1 + F2) are replaced with Zeros.

Hourly time series

I. Log transforming the time series : log(ts)
II. Applying TBATS() [3] on the log transformed time series for the initial forecasts (F1). (setting seasonal.periods=c(24,168,8766))
III. Applying LSTM algorithm to each type (i.e. Demographic, Finance etc.) separately as different models, according to [2] (**excluding** the log transformation and STL decomposition) on the residuals generated by (ii) method. (F2)
IV. Adding the residual forecasts to the base forecasts (F1 + F2) to generate the final forecasts.
V. Forecasts that are negative after the addition (F1 + F2) are replaced with Zeros.

Please note that the final forecasts are back transformed using the exponential function exp()

References

[1] Hyndman R, Bergmeir C, Caceres G, Chhay L, O'Hara-Wild M, Petropoulos F, Razbash S, Wang E and Yasmeen F (2018).
forecast: Forecasting functions for time series and linear models. R package version 8.3, <URL:http://pkg.robjhyndman.com/forecast>.

[2] K. Bandara, C. Bergmeir, and S. Smyl, “Forecasting across time series databases using long short-term memory networks on groups of similar series,” arXiv preprint arXiv:1710.03222, 2017

[3] Alysha M De Livera, Rob J Hyndman, Ralph D Snyder (2011) Journal of the American Statistical Association 106(496), 1513-1527