

Universal Forecasting Scheme

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Abstract

In this research investigation, the author has detailed a novel method of forecasting.

Theory

Firstly, we define the definitions of Similarity and Dissimilarity using author's [1] as follows:
Given any two real numbers a and b, their Similarity is given by

$$\text{Similarity}(a,b) = \begin{cases} a^2 & \text{if } a < b \\ b^2 & \text{if } b < a \end{cases}$$

and their Dissimilarity is given by

$$\text{Dissimilarity}(a,b) = \begin{cases} ab - a^2 & \text{if } a < b \\ ab - b^2 & \text{if } b < a \end{cases}$$

Given any time series or non-time series sequence of the kind

$$S = \{y_1, y_2, y_3, \dots, y_{n-1}, y_n\}$$

We can now write y_{n+1} as

$$y_{(n+1)} = y_{(n+1)S} + y_{(n+1)DS} \text{ where}$$

$$y_{(n+1)S} = \sum_{i=1}^n y_i \left\{ \frac{\sum_{\substack{j=1 \\ j \neq i}}^n \left(\frac{\text{Total Exhaustive Similarity}(y_i, y_j)}{\text{Total Exhaustive Similarity}(y_i, y_j) + \text{Total Exhaustive Dissimilarity}(y_i, y_j)} \right)}{\sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \left(\frac{\text{Total Exhaustive Similarity}(y_i, y_j)}{\text{Total Exhaustive Similarity}(y_i, y_j) + \text{Total Exhaustive Dissimilarity}(y_i, y_j)} \right)} \right\}$$

and

$$y_{(n+1)DS} = \sum_{i=1}^n y_i \left\{ \frac{\sum_{\substack{j=1 \\ j \neq i}}^n \left(\frac{\text{Total Exhaustive Dissimilarity}(y_i, y_j)}{\text{Total Exhaustive Similarity}(y_i, y_j) + \text{Total Exhaustive Dissimilarity}(y_i, y_j)} \right)}{\sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \left(\frac{\text{Total Exhaustive Dissimilarity}(y_i, y_j)}{\text{Total Exhaustive Similarity}(y_i, y_j) + \text{Total Exhaustive Dissimilarity}(y_i, y_j)} \right)} \right\}$$

The definitions of Total Exhaustive Similarity and Total Exhaustive Dissimilarity are detailed as follows:

Total Exhaustive Similarity $(y_i, y_j) = \text{Similarity}(y_i, y_j) + \text{Similarity}(S_1, S_2) +$
 $\text{Similarity}(S_3, S_4) + \text{Similarity}(S_4, S_5) + \dots + \text{Similarity}(S_k, S_{k+1})$ till $S_k = S_{k+1}$
 where $S_1 = \{\text{Smaller}(y_i, y_j)\}$ and $S_2 = \{\text{Larger}(y_i, y_j) - \text{Smaller}(y_i, y_j)\}$
 where $S_3 = \{\text{Smaller}(S_1, S_2)\}$ and $S_4 = \{\text{Larger}(S_1, S_2) - \text{Smaller}(S_1, S_2)\}$
 where $S_4 = \{\text{Smaller}(S_3, S_4)\}$ and $S_5 = \{\text{Larger}(S_3, S_4) - \text{Smaller}(S_3, S_4)\}$

and so on so forth.

Total Exhaustive Dissimilarity $(y_i, y_j) = \text{Dissimilarity}(y_i, y_j) + \text{Dissimilarity}(S_1, S_2) +$
 $\text{Dissimilarity}(S_3, S_4) + \text{Dissimilarity}(S_4, S_5) + \dots + \text{Dissimilarity}(S_k, S_{k+1})$ till $S_k = S_{k+1}$
 where $S_1 = \{\text{Smaller}(y_i, y_j)\}$ and $S_2 = \{\text{Larger}(y_i, y_j) - \text{Smaller}(y_i, y_j)\}$
 where $S_3 = \{\text{Smaller}(S_1, S_2)\}$ and $S_4 = \{\text{Larger}(S_1, S_2) - \text{Smaller}(S_1, S_2)\}$
 where $S_4 = \{\text{Smaller}(S_3, S_4)\}$ and $S_5 = \{\text{Larger}(S_3, S_4) - \text{Smaller}(S_3, S_4)\}$

and so on so forth.

References

1. http://vixra.org/author/ramesh_chandra_bagadi