# 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

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

and their Dissimilarity is given by

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

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

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

We can now write $y_{n+1}$ as

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

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

and

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

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

$$
\begin{aligned}
&Total\ Exhaustive\ Similarity(y_i, y_j) = Similarity(y_i, y_j) + Similarity(S_1, S_2) + \\
&Similarity(S_3, S_4) + Similarity(S_4, S_5) + \ldots\ldots + Similarity(S_k, S_{k+1})\ till\ S_k = S_{k+1} \\
&where\ S_1 = \{Smaller(y_i, y_j)\}\ and\ S_2 = \{L\arg er(y_i, y_j) - Smaller(y_i, y_j)\} \\
&where\ S_3 = \{Smaller(S_1, S_2)\}\ and\ S_4 = \{L\arg er(S_1, S_2) - Smaller(S_1, S_2)\} \\
&where\ S_4 = \{Smaller(S_3, S_4)\}\ and\ S_5 = \{L\arg er(S_3, S_4) - Smaller(S_3, S_4)\} \\
&\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&and\ so\ on\ so\ forth.
\end{aligned}
$$

$$
\begin{aligned}
&Total\ Exhaustive\ Dissimilar\ ity(y_i, y_j) = Dissimilar\ ity(y_i, y_j) + Dissimilar\ ity(S_1, S_2) + \\
&Dissimilar\ ity(S_3, S_4) + Dissimilar\ ity(S_4, S_5) + \ldots\ldots + Dissimilar\ ity(S_k, S_{k+1})\ till\ S_k = S_{k+1} \\
&where\ S_1 = \{Smaller(y_i, y_j)\}\ and\ S_2 = \{L\arg er(y_i, y_j) - Smaller(y_i, y_j)\} \\
&where\ S_3 = \{Smaller(S_1, S_2)\}\ and\ S_4 = \{L\arg er(S_1, S_2) - Smaller(S_1, S_2)\} \\
&where\ S_4 = \{Smaller(S_3, S_4)\}\ and\ S_5 = \{L\arg er(S_3, S_4) - Smaller(S_3, S_4)\} \\
&\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&and\ so\ on\ so\ forth.
\end{aligned}
$$

Similarly, we can write the Total Exhaustive Similarity and Total Exhaustive Dissimilarity for $(y_r, y_j)$

## References


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