# The Recursive Future Equation And The Recursive Past Equation Based On The Ananda-Damayanthi Normalized Similarity Measure

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**Technical Note**

**Abstract**

In this research Technical Note the author have presented a Recursive Future Equation and Recursive Past Equation to find one Step Future Element or a one Step Past Element of a given Time Series data Set.

**Theory**

Note that from [1], the Recursive Future Average Of A Time Series Data Based on Cosine Similarity can be given by the following methods:

*Method 1:*

$$y_{n+1} = \frac{\sum_{i=1}^{n}(y_i)\{CS(y_i, y_{n+1})\}}{\left\{\sum_{i=1}^{n}\left(\{CS(y_i, y_{n+1})\}^2\right)\right\}^{1/2}}$$

where $CS(y_i, y_{n+1}) = \left\{\frac{Smaller\ \ of\ \ (y_i, y_{n+1})}{Larger\ \ of\ \ (y_i, y_{n+1})}\right\}$

when the Time Series Data is of the kind

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

*Method 2:*

$$y_{n+1} = \frac{\sum_{i=1}^{n}(y_i)\{CS(y_i, y_{n+1})\}\{CS(y_i, y_{n+1})\}}{\sum_{i=1}^{n}\{CS(y_i, y_{n+1})\}}$$

where $CS(y_i, y_{n+1}) = \left\{ \frac{Smaller\ \ of\ \ (y_i, y_{n+1})}{Larger\ \ of\ \ (y_i, y_{n+1})} \right\}$

when the Time Series Data is of the kind

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

Deriving motivation from this concept we extend this concept thusly as follows:

*The Recursive Future Equation*

*Method 1:*

Here, the given Time Series is $S = \{y_1, y_2, y_3, \ldots\ldots, y_{n-1}, y_n\}$ and we need to find $y_{n+1}$.

$$y_{n+1} = \frac{\sum_{j=1}^{\infty}\sum_{i=1}^{n}(y_{i\,j})\{CS(y_{i\,j}, y_{n+1})\}}{\left\{\sum_{j=1}^{\infty}\sum_{i=1}^{n}\left(\{CS(y_{i\,j}, y_{n+1})\}^2\right)\right\}^{1/2}}$$

$$y_{i\,j} = Larger\ of\ (y_{n+1}, y_{i(j-1)}) - Smaller\ of\ (y_{n+1}, y_{i(j-1)})$$

where especially, $y_{i\,(j=1)} = Larger\ of\ (y_{n+1}, y_i) - Smaller\ of\ (y_{n+1}, y_i)$ and

similarly, $CS(y_{i\,j}, y_{n+1}) = \left( \frac{Smaller\ of\ (y_{n+1}, y_{i\,j})}{Larger\ of\ (y_{n+1}, y_{i\,j})} \right)$

where especially, $CS(y_{i(j=1)}, y_{n+1}) = \left( \frac{Smaller\ of\ (y_{n+1}, y_i)}{Larger\ of\ (y_{n+1}, y_i)} \right)$

And, $\infty$ for each $y_i$ term is defined such that, it is the positive integral number at which the ratio $CS(y_{i\,j}, y_{n+1}) = \left( \frac{Smaller\ of\ (y_{n+1}, y_{i\,j})}{Larger\ of\ (y_{n+1}, y_{i\,j})} \right)$ tends to zero.

*The Recursive Past Equation*

*Method 1:*

Here, the given Time Series is $S = \{y_1, y_2, y_3, \ldots\ldots, y_{n-1}, y_n\}$ and we need to find $y_0$.

$$y_n = \frac{\sum_{j=1}^{\infty}\sum_{i=0}^{n-1}(y_{i\,j})\{CS(y_{i\,j}, y_n)\}}{\left\{\sum_{j=1}^{\infty}\sum_{i=0}^{n-1}\left(\{CS(y_{i\,j}, y_n)\}^2\right)\right\}^{1/2}}$$

$$y_{i\,j} = Larger\ of\ (y_n, y_{i(j-1)}) - Smaller\ of\ (y_n, y_{i(j-1)})$$

where especially, $y_{i\,(j=1)} = Larger\ of\ (y_n, y_i) - Smaller\ of\ (y_n, y_i)$ and

similarly, $CS(y_{i\,j}, y_n) = \left( \frac{Smaller\ of\ (y_n, y_{i\,j})}{Larger\ of\ (y_n, y_{i\,j})} \right)$

where especially, $CS(y_{i\,(j=1)}, y_n) = \left( \frac{Smaller\ of\ (y_n, y_i)}{Larger\ of\ (y_n, y_i)} \right)$

And, $\infty$ for each $y_i$ term is defined such that, it is the positive integral number at which the ratio $CS(y_{i\,j}, y_n) = \left( \frac{Smaller\ of\ (y_n, y_{i\,j})}{Larger\ of\ (y_n, y_{i\,j})} \right)$ tends to zero.

**References**


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