The Recursive Future And Past Equation Based On The Ananda-Damayanthi Normalized Similarity Measure Considered To Exhaustion

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Author:
Ramesh Chandra Bagadi

Affiliation 1:

Data Scientist

International School Of Engineering (INSOFE)

2nd Floor, Jyothi Imperial, Vamsiram Builders, Janardana Hills, Above South India Shopping Mall, Old Mumbai Highway, Gachibowli, Hyderabad, TelanganaState, 500032, India.

Email:
ramesh.bagadi@insofe.edu.in

Affiliation 2:

Founder & Owner

tex*N* Consulting Private Limited, Gayatrinagar, Jilleleguda, Hyderabad, Telengana State, 500097, India.

Email:

rameshcbagadi@

uwalumni.com

Affiliation 3:

Founder & Owner

Ramesh Bagadi Consulting LLC (R420752),

Madison, Wisconsin-53715, United States Of America.

Email:

rameshcbagadi@

uwalumni.com

Abstract

In this research investigation, the author has presented a Recursive Past Equation and a Recursive Future Equation based on the Ananda-Damayanthi Normalized Similarity Measure considered to Exhaustion [1].

The Recursive Future Equation

Given a Time Series $Y = \{y_1, y_2, y_3, \ldots\ldots, y_{n-1}, y_n\}$

we can find y_{n+1} using the following Recursive Future Equation

$$y_{n+1} = \underset{p\to\infty}{Limit} \frac{\left\{\sum_{k=1}^{n} y_k \left\{\left\{\frac{S_k}{L_k}\right\} + \left\{\frac{S_{k+1}}{L_{k+1}}\right\} + \left\{\frac{S_{k+2}}{L_{k+2}}\right\} + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\} + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}\right\}\right\}}{\sqrt{\sum_{k=1}^{n}\left\{\left\{\frac{S_k}{L_k}\right\}^2 + \left\{\frac{S_{k+1}}{L_{k+1}}\right\}^2 + \left\{\frac{S_{k+2}}{L_{k+2}}\right\}^2 + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\}^2 + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}^2\right\}}}$$

where

$S_k = Smaller\ of\ (y_{n+1}, y_k)$ and $L_k = Larger\ of\ (y_{n+1}, y_k)$

$S_{k+1} = Smaller\ of\ ((L_k - S_k), y_k)$ and $L_{k+1} = Larger\ of\ ((L_k - S_k), y_k)$

$S_{k+2} = Smaller\ of\ ((L_{k+1} - S_{k+1}), y_k)$ and $L_{k+2} = Larger\ of\ ((L_{k+1} - S_{k+1}), y_k)$

$S_{k+p-1} = Smaller\ of\ ((L_{k+p-2} - S_{k+p-2}), y_k)$ and $L_{k+p-1} = Larger\ of\ ((L_{k+p-2} - S_{k+p-2}), y_k)$

$S_{k+p} = Smaller\ of\ ((L_{k+p-1} - S_{k+p-1}), y_k)$ and $L_{k+p} = Larger\ of\ ((L_{k+p-1} - S_{k+p-1}), y_k)$

where p is a Number which makes the aforementioned Difference Residual $(L_{k+p-1} - S_{k+p-1})$ tend to Zero.

From the above Recursive Equation, we can solve for y_{n+1}.

Proof:

We consider y_1 and find the Ananda-Damayanthi Similarity [1] between y_1 and y_{n+1} which turns out to be $\left\{\frac{S_1}{L_1}\right\}$. We now consider the lack of similarity part, i.e., $(L_1 - S_1)$ and again find the Similarity between y_1 and $(L_1 - S_1)$ which turns out to be $\left\{\frac{S_{1+1}}{L_{1+1}}\right\} = \left\{\frac{S_2}{L_2}\right\}$. And similarly, we find $\left\{\frac{S_{1+2}}{L_{1+2}}\right\} = \left\{\frac{S_3}{L_3}\right\}$, $\left\{\frac{S_{1+3}}{L_{1+3}}\right\} = \left\{\frac{S_4}{L_4}\right\}$, ……….., $\left\{\frac{S_{1+p-1}}{L_{1+p-1}}\right\} = \left\{\frac{S_p}{L_p}\right\}$, $\left\{\frac{S_{1+p}}{L_{1+p}}\right\}$. We now add them all. Similarly, we consider y_2, y_3,….., upto y_{n-1} and y_n and compute such aforementioned quantities and add them all. We now Normalize, i.e., divide each of this value by the quantity $\sqrt{\sum_{k=1}^{n}\left\{\left\{\frac{S_k}{L_k}\right\}^2 + \left\{\frac{S_{k+1}}{L_{k+1}}\right\}^2 + \left\{\frac{S_{k+2}}{L_{k+2}}\right\}^2 + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\}^2 + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}^2\right\}}$. We equate this value to y_{n+1} as the RHS is the Total Normalized Similarity contribution from each element of the Time Series Set $Y = \{y_1, y_2, y_3, \ldots\ldots, y_{n-1}, y_n\}$ with respect to y_{n+1}.

General Form

We can note that the above equation

$$y_{n+1} = \underset{p\to\infty}{Limit} \frac{\left\{\sum_{k=1}^{n} y_k \left\{\left\{\frac{S_k}{L_k}\right\} + \left\{\frac{S_{k+1}}{L_{k+1}}\right\} + \left\{\frac{S_{k+2}}{L_{k+2}}\right\} + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\} + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}\right\}\right\}}{\sqrt{\sum_{k=1}^{n}\left\{\left\{\frac{S_k}{L_k}\right\}^2 + \left\{\frac{S_{k+1}}{L_{k+1}}\right\}^2 + \left\{\frac{S_{k+2}}{L_{k+2}}\right\}^2 + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\}^2 + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}^2\right\}}}$$

is in general of the form

$$y_{n+1} = \underset{p\to\infty}{Limit} \frac{\left\{a_1 y_{n+1} + \frac{a_2}{y_{n+1}}\right\}}{\sqrt{\left\{(a_3 y_{n+1})^2 + \left(\frac{a_4}{y_{n+1}}\right)^2\right\}}}$$

where, a_1, a_2, a_3 and a_4 are some positive integers.

We can further write the above equation as

$$(y_{n+1})^2 \left\{(a_3 y_{n+1})^2 + \left(\frac{a_4}{y_{n+1}}\right)^2\right\} = \left\{a_1 y_{n+1} + \frac{a_2}{y_{n+1}}\right\}^2$$

$$(a_3)^2(y_{n+1})^6-(a_1)^2(y_{n+1})^4+\{(a_4)^2-(2a_1a_2)\}(y_{n+1})^2-(a_2)^2=0 \qquad \text{Equation A}$$

Defining Error

We define Error in the following fashion:

For the Recursive Future Equation:

Method 1

Given a Time Series $Y=\{y_1,y_2,y_3,.......,y_{n-1},y_n\}$ we consider only $Y=\{y_1,y_2,y_3,.......,y_{n-1}\}$ and use the aforementioned Recursive Future Equation to find the n^{th} term. Say this is ${}^p y_n$ where the p stands for the 'predicted' or 'forecasted' value. Then, the Error is defined by

$$\varepsilon_F=\left(\frac{y_n-{}^p y_n}{y_n}\right)$$

Method 2

Given a Time Series $Y=\{y_1,y_2,y_3,.......,y_{n-1},y_n\}$ we consider it and use the aforementioned Recursive Future Equation to find the $(n+1)^{th}$ term. Say this is ${}^p y_{n+1}$ where the p stands for the 'predicted' or 'forecasted' value. We now consider the Time Series Set $Y=\{y_2,y_3,.......,y_{n-1},y_n,y_{n+1}\}$ and use the aforementioned Recursive Past Equation to generate the term previous to y_2, i.e., ${}^p y_1$. Then, the Error is defined by

$$\varepsilon_F = \left(\frac{y_1 - {}^p y_1}{y_1} \right)$$

Therefore, simple Error can be given by

$$\varepsilon_F = \left(y_1 - {}^p y_1 \right) = \left\{ y_1 - Desired\ \ Root\ Of \left\{ \begin{matrix} (c_3)^2 (y_{n+1})^6 - (c_1)^2 (y_{n+1})^4 + \\ \{(c_4)^2 - (2c_1 c_2)\}(y_{n+1})^2 - (c_2)^2 = 0 \end{matrix} \right\} \right\}$$

where the Equation $(c_3)^2 (y_{n+1})^6 - (c_1)^2 (y_{n+1})^4 + \{(c_4)^2 - (2c_1 c_2)\}(y_{n+1})^2 - (b_2)^2 = 0$ is analogously developed as equation B using the Time Series Set $Y = \{y_2, y_3, \ldots\ldots, y_{n-1}, y_n, y_{n+1}\}$ to find y_1, where where, c_1, c_2, c_3 and c_4 are some positive integers.

The Functional Form Equation For Making Future Forecast

We consider the equation shown below

$$\varepsilon_F = \left(y_1 - {}^p y_1 \right) = \left\{ y_1 - Desired\ \ Root\ Of \left\{ \begin{matrix} (c_3)^2 (y_{n+1})^6 - (c_1)^2 (y_{n+1})^4 + \\ \{(c_4)^2 - (2c_1 c_2)\}(y_{n+1})^2 - (c_2)^2 = 0 \end{matrix} \right\} \right\}$$

and minimize the Error w.r.t y_{n+1}, i.e.,

$\frac{d\varepsilon_F}{dy_{n+1}} = 0$ with $\frac{d^2\varepsilon_F}{dy_{n+1}{}^2} > 0$ at the value of $y_{n+1}\big|_{\varepsilon_F \min}$ where is ε_F minimum. The Equation at which this error is Minimum i.e., $\left.\frac{d\varepsilon_F}{dy_{n+1}} = 0\right|_{\varepsilon_F\ Min}$ can be used to re-calculate the a_1, a_2, a_3 and a_4 and say these are a_{1new}, a_{2new}, a_{3new} and a_{4new}, The Functional Form Equation For Making Future Forecast becomes

$$(a_{3new})^2(y_{n+1})^6 - (a_{1new})^2(y_{n+1})^4 + \{(a_{4new})^2 - (2a_{1new}a_{2new})\}(y_{n+1})^2 - (a_{2new})^2 = 0$$

The Recursive Past Equation

Given a Time Series $Y = \{y_1, y_2, y_3, \ldots\ldots, y_{n-1}, y_n\}$

we can find y_0 using the following Recursive Past Equation

$$y_n = \underset{p\to\infty}{Limit} \frac{\left\{\sum_{k=0}^{n-1} y_k \left\{\left\{\frac{S_k}{L_k}\right\} + \left\{\frac{S_{k+1}}{L_{k+1}}\right\} + \left\{\frac{S_{k+2}}{L_{k+2}}\right\} + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\} + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}\right\}\right\}}{\sqrt{\sum_{k=0}^{n-1}\left\{\left\{\frac{S_k}{L_k}\right\}^2 + \left\{\frac{S_{k+1}}{L_{k+1}}\right\}^2 + \left\{\frac{S_{k+2}}{L_{k+2}}\right\}^2 + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\}^2 + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}^2\right\}}}$$

where

$S_k = Smaller\ of\ (y_n, y_k)$ and $L_k = Larger\ of\ (y_n, y_k)$

$S_{k+1} = Smaller\ of\ ((L_k - S_k), y_k)$ and $L_{k+1} = Larger\ of\ ((L_k - S_k), y_k)$

$$S_{k+2} = Smaller\ of\ \left(\left(L_{k+1} - S_{k+1}\right), y_k\right) \text{ and } L_{k+2} = Larger\ of\ \left(\left(L_{k+1} - S_{k+1}\right), y_k\right)$$

$$S_{k+p-1} = Smaller\ of\ \left(\left(L_{k+p-2} - S_{k+p-2}\right), y_k\right) \text{ and } L_{k+p-1} = Larger\ of\ \left(\left(L_{k+p-2} - S_{k+p-2}\right), y_k\right)$$

$$S_{k+p} = Smaller\ of\ \left(\left(L_{k+p-1} - S_{k+p-1}\right), y_k\right) \text{ and } L_{k+p} = Larger\ of\ \left(\left(L_{k+p-1} - S_{k+p-1}\right), y_k\right)$$

where p is a Number which makes the aforementioned Difference Residual $\left(L_{k+p-1} - S_{k+p-1}\right)$ tend to Zero.

From the above Recursive Equation, we can solve for y_0.

Proof:

We consider y_0 and slate the Ananda-Damayanthi Similarity [1] between y_0 and y_n which turns out to be $\left\{\frac{S_0}{L_0}\right\}$. We now consider the lack of similarity part, i.e., $\left(L_0 - S_0\right)$ and again find the Similarity between y_0 and $\left(L_0 - S_0\right)$ which turns out to be $\left\{\frac{S_{0+1}}{L_{0+1}}\right\} = \left\{\frac{S_1}{L_1}\right\}$. And similarly, we find $\left\{\frac{S_{0+2}}{L_{0+2}}\right\} = \left\{\frac{S_2}{L_2}\right\}$, $\left\{\frac{S_{0+3}}{L_{0+3}}\right\} = \left\{\frac{S_3}{L_3}\right\}$, ………., $\left\{\frac{S_{0+p-1}}{L_{0+p-1}}\right\} = \left\{\frac{S_{p-1}}{L_{p-1}}\right\}$, $\left\{\frac{S_{0+p}}{L_{0+p}}\right\} = \left\{\frac{S_p}{L_p}\right\}$. We now add them all. Similarly, we consider y_2, y_3,……, upto y_{n-1} and compute such aforementioned quantities and add them all. We now Normalize, i.e., divide each of this value by the quantity $\sqrt{\sum_{k=0}^{n-1}\left\{\left\{\frac{S_k}{L_k}\right\}^2 + \left\{\frac{S_{k+1}}{L_{k+1}}\right\}^2 + \left\{\frac{S_{k+2}}{L_{k+2}}\right\}^2 + \ldots\ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\}^2 + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}^2\right\}}$. We equate this value to y_n

as the RHS is the Total Normalized Similarity contribution from each element of the Time Series Set $Y = \{y_0, y_1, y_2, y_3, \ldots\ldots, y_{n-1}\}$ with respect to y_n.

General Form

We can note that the above equation

$$y_n = \underset{p\to\infty}{Limit} \frac{\left\{\sum_{k=0}^{n-1} y_k \left\{\left\{\frac{S_k}{L_k}\right\} + \left\{\frac{S_{k+1}}{L_{k+1}}\right\} + \left\{\frac{S_{k+2}}{L_{k+2}}\right\} + \ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\} + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}\right\}\right\}}{\sqrt{\sum_{k=0}^{n-1}\left\{\left\{\frac{S_k}{L_k}\right\}^2 + \left\{\frac{S_{k+1}}{L_{k+1}}\right\}^2 + \left\{\frac{S_{k+2}}{L_{k+2}}\right\}^2 + \ldots\ldots + \left\{\frac{S_{k+p-1}}{L_{k+p-1}}\right\}^2 + \left\{\frac{S_{k+p}}{L_{k+p}}\right\}^2\right\}}}$$

is in general of the form

$$y_n = \frac{\left\{b_1 y_n + \frac{b_2}{y_n}\right\}}{\sqrt{\left\{(b_3 y_n)^2 + \left(\frac{b_4}{y_n}\right)^2\right\}}}$$

where, b_1, b_2, b_3 and b_4 are some positive integers.

We can further write the above equation as

$$(y_n)^2\left\{(b_3 y_n)^2+\left(\frac{b_4}{y_n}\right)^2\right\}=\left\{b_1 y_n+\frac{b_2}{y_n}\right\}^2$$

$$(b_3)^2(y_n)^6-(b_1)^2(y_n)^4+\{(b_4)^2-(2b_1b_2)\}(y_n)^2-(b_2)^2=0 \qquad \text{Equation B}$$

where, b_1, b_2, b_3 and b_4 are some positive integers.

Defining Error

We define Error in the following fashion:

For the Recursive Past Equation:

Method 1

Given a Time Series $Y=\{y_1, y_2, y_3, \ldots\ldots., y_{n-1}, y_n\}$ we consider only $Y=\{y_2, y_3, \ldots\ldots., y_{n-1}, y_n\}$ and use the aforementioned Recursive Future Past to find the 1^{st} term. Say this is ${}^{p}y_1$ where the p stands for the 'predicted' or 'forecasted' value. Then, the Error is defined by

$$\varepsilon_P=\left(\frac{y_1-{}^{p}y_1}{y_1}\right)$$

Method 2

Given a Time Series $Y=\{y_1, y_2, y_3, \ldots\ldots., y_{n-1}, y_n\}$ we consider it and use the aforementioned Recursive Future Equation to find the term previous to y_1. Say this is ${}^{p}y_0$ where the p stands for the 'predicted' or 'forecasted' value. We now consider the Time Series Set $Y=\{y_0, y_1, y_2, y_3, \ldots\ldots, y_{n-1}\}$ and use the aforementioned Recursive Future Equation to generate the term next to y_{n-1}, i.e., ${}^{p}y_n$. Then, the Error is defined by

$$\varepsilon_F = \left(\frac{y_n - {}^{p}y_n}{y_n}\right)$$

Functional Form Equation For Making Past Forecast

A Seasoned reader of author Literature, especially the section on '*Functional Form Equation For Making Future Forecast'* can infer the procedure for the Past Forecast which is very much similar to the Future Forecast.

Computation Complexity

For the World's fastest Chineese Super-Computer which can compute 33,870 Trillion Computations per second we can use the equation

$2^n + m(2^n) = 33870 \times 10^9$ to calculate the Maximum Number of Terms of the Time Series n for which we wish to predict the $(n+1)^{th}$ term and m is the Number Of Difference Residual Terms we wish to consider for each term, to find the n for a given m so that the $(n+1)^{th}$ term is computed in one second.

Furthermore, if we take $m=3$ and for different amounts of times we can spare for getting the computed answer, the Number of Terms of the Time Series n that we can consider is given below:

Serial Number	*Duration Of Computation*	*Number of Terms To Consider*
1	1 Second	43.36011
2	1 Hour	55.17389
3	1 Day	59.75885
4	1 Week	62.56621
5	1 Month (31 Days)	64.71305
6	1 Year	68.27061

References

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