

The Recursive Future Equation Based On The Ananda-Damayanthi Normalized Similarity Measure. {File Closing Version 4}. ISSN 1751-3030

Author:

Ramesh Chandra Bagadi

Data Scientist

INSOFE (International School Of Engineering)

Hyderabad, India.

rameshcbagadi@uwalumni.com

+91 9440032711

Technical Note

Abstract

In this research Technical Note the author have presented a Recursive Future Average Of A Time Series Data Based on Cosine Similarity.

Theory

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

when the Time Series Data is of the kind

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

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

when the Time Series Data is of the kind

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

Deriving motivation from this concept [2], we further extend this formula using [1] as

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

$$\text{where } {}^1y_i = \frac{\{y_i y_{n+1} - (\text{Smaller of } (y_i, y_{n+1}))^2\}}{y_{n+1}} \text{ and}$$

Model 1:

$${}^2y_i = \frac{\{y_i y_{n+1} - (\text{Smaller of } ({}^1y_i, y_{n+1}))^2\}}{y_{n+1}}, \dots, \text{i.e., and so on, so forth}$$

$${}^k y_i = \frac{\{y_i y_{n+1} - (\text{Smaller of } ({}^{k-1}y_i, y_{n+1}))^2\}}{y_{n+1}}$$

upto

$${}^r y_i = \frac{\{y_i y_{n+1} - (\text{Smaller of } ({}^{r-1}y_i, y_{n+1}))^2\}}{y_{n+1}} \text{ such that we can write}$$

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

where r is a number such that ${}^r y_i \rightarrow 0$.

Model 2:

where ${}^1y_i = \{Larger(y_{n+1}, y_i) - Smaller(y_{n+1}, y_i)\}$ and

${}^2y_i = \{Larger(y_{n+1}, {}^1y_i) - Smaller(y_{n+1}, {}^1y_i)\}, \dots, \text{i.e., and so on, so forth}$

${}^k y_i = \{Larger(y_{n+1}, {}^{k-1}y_i) - Smaller(y_{n+1}, {}^{k-1}y_i)\}$

upto

${}^r y_i = \{Larger(y_{n+1}, {}^{r-1}y_i) - Smaller(y_{n+1}, {}^{r-1}y_i)\}$ such that we can write

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

where r is a number such that ${}^r y_i \rightarrow 0$.

Model 3:

where ${}^1 y_i = Larger \frac{\{y_i y_{n+1} - (Smaller of (y_i, y_{n+1}))^2\}}{Larger of (y_i, y_{n+1})}$ and

${}^2 y_i = \frac{\{{}^1 y_i y_{n+1} - (Smaller of ({}^1 y_i, y_{n+1}))^2\}}{Larger of ({}^1 y_i, y_{n+1})}, \dots, \text{i.e., and so on, so forth}$

${}^k y_i = \frac{\{{}^{k-1} y_i y_{n+1} - (Smaller of ({}^{k-1} y_i, y_{n+1}))^2\}}{Larger of ({}^{k-1} y_i, y_{n+1})}$

upto

${}^r y_i = \frac{\{{}^{r-1} y_i y_{n+1} - (Smaller of ({}^{r-1} y_i, y_{n+1}))^2\}}{Larger of ({}^{r-1} y_i, y_{n+1})}$ such that we can write

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

where r is a number such that ${}^r y_i \rightarrow 0$.

Bagadi, R. (2017). The Recursive Future Equation Based On The Ananda-Damayanthi Normalized Similarity Measure. {File Closing Version 4}. ISSN 1751-3030. *PHILICA.COM Article number 1129*.
http://philica.com/display_article.php?article_id=1129

References

1. Bagadi, R. (2016). Proof Of As To Why The Euclidean Inner Product Is A Good Measure Of Similarity Of Two Vectors. *PHILICA.COM Article number 626*.
http://philica.com/display_article.php?article_id=626
2. Bagadi, R. (2017). Recursive Future Average Of A Time Series Data Based On Cosine Similarity. ISSN 1751-3030. *PHILICA.COM Article number 1075*.
http://philica.com/display_article.php?article_id=1075
3. <http://www.philica.com/advancedsearch.php?author=12897>
4. http://www.vixra.org/author/ramesh_chandra_bagadi