Bagadi, R. (2017). Universal One Step Forecasting Model For Dynamical State Systems (Version 4). ISSN 1751-3030. *PHILICA.COM Article number 965*.

http://www.philica.com/display_article.php?article_id=965

Universal One Step Forecasting Model For Dynamical State Systems (Version 4). ISSN 1751-3030.

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Published in matho.philica.com

Abstract

In this research investigation, the author has presented a Novel Forecasting Model based on Locally Linear Transformations, Element Wise Inner Product Mapping, De-Normalization of the Normalized States for predicting the next instant of a Dynamical State given its sufficient history is known.

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Universal One Step Forecasting Model For Dynamical State Systems (Version 3)

ISSN 1751 - 3030

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Abstract

In this research investigation, the author has presented a Novel Forecasting Model based on Locally Linear Transformations, Element Wise Inner Product Mapping, De-Normalization of the Normalized States for predicting the next instant of a Dynamical State given its sufficient history is known.

Theory

Prediction of the Direction of the Dynamic State Vector $\hat{X}_1\left(t_{(n+1)}\right)$

Model 1

Consider a Dynamical State System denoted by $\overline{X}_1\left(t_i\right)$ for which we know the data for $i=1$ to n.

$\overline{X}_1\left(t_i\right)$ is a Row Vector with m Number of Elements wherein each element denotes the Value taken by the respective Parameter (among the m Parameters) of concern as i goes from 1 to n.

We denote the j^{th} element of $\overline{X}_1\left(t_i\right)$ as $X_1\left(t_{ij}\right)$ where $1 \leq j \leq m$

We Normalize (Simple Vector Normalization) all State Vectors $\overline{X}_1\left(t_i\right)$ where $1 \leq j \leq m$ and $1 \leq i \leq n$ and represent them by $\hat{X}_1\left(t_i\right)$

We define $T_{1\{i \to (i+1)\}}$ as an $m \times m$ Square Matrix where all its diagonal elements are given by

$$T_{1\{i\rightarrow(i+1)\}}(j,j)=\frac{\hat{X}_1\left(t_{(i+1)j}\right)}{\hat{X}_1\left(t_{ij}\right)} \quad [1]$$

And all the off diagonal elements of $T_{1\{i\rightarrow(i+1)\}}$ are zero.

Now, we consider

$\hat{X}_1(t_n)$ and find the Euclidean Inner Product of $\hat{X}_1(t_n)$ and $\hat{X}_1(t_k)$, i.e., find

$\hat{X}_1(t_n)\cdot\hat{X}_1(t_k)$ for $k=1$ to $(n-1)$. We now find the index (as k runs from 1 to $(n-1)$) at which the maximum value of the Inner Product occurs. Let this index be l.

That is $\hat{X}_1(t_n)\cdot\hat{X}_1(t_l)=\max\left\{\hat{X}_1(t_n)\cdot\hat{X}_1(t_k)\right\}$ [2]

for $k=1$ to $(n-1)$ and $1\leq l\leq(n-1)$.

We now write

$$\hat{X}_1\left(t_{(n+1)j}\right)=\hat{X}_1\left(t_{nj}\right)\left\{T_{1\{l\rightarrow(l+1)\}}(j,j)\right\} \quad [3]$$

Model 2

Consider a Dynamical State System denoted by $\overline{X}_1(t_i)$ for which we know the data for $i=1$ to n.

$\overline{X}_1(t_i)$ is a Row Vector with m Number of Elements wherein each element denotes the Value taken by the respective Parameter (among the m Parameters) of concern as i goes from 1 to n.

We denote the j^{th} element of $\overline{X}_1(t_i)$ as $X_1(t_{ij})$ where $1\leq j\leq m$

We Normalize (Simple Vector Normalization) all State Vectors $\overline{X}_1(t_i)$ where $1\leq j\leq m$ and $1\leq i\leq n$ and represent them by $\hat{X}_1(t_i)$

We define $T_{1\{i\rightarrow(i+1)\}}$ as an $m\times m$ Square Matrix where all its diagonal elements are given by

$$T_{1\{i\to(i+1)\}}(j,j)=\frac{\hat{X}_1\left(t_{(i+1)j}\right)}{\hat{X}_1\left(t_{ij}\right)}$$

And all the off diagonal elements of $T_{1\{i\to(i+1)\}}$ are zero.

Now, we consider

$\hat{X}_1\left(t_{nj}\right)$ and compare $\hat{X}_1\left(t_{nj}\right)$ and $\hat{X}_1\left(t_{kj}\right)$, i.e., find

$\left|\hat{X}_1\left(t_{nj}\right)-\hat{X}_1\left(t_{kj}\right)\right|$ for $k=1$ to $(n-1)$. We now find the index (as k runs from 1 to $(n-1)$) at which the minimum value of the aforementioned difference term, $\left|\hat{X}_1\left(t_{nj}\right)-\hat{X}_1\left(t_{kj}\right)\right|$ occurs. Let this index be p_j.

That is $\left|\hat{X}_1\left(t_{nj}\right)-\hat{X}_1\left(t_{(p_j)j}\right)\right|=\min\left\{\left|\hat{X}_1\left(t_{nj}\right)-\hat{X}_1\left(t_{kj}\right)\right|\right\}$ [4]

for $k=1$ to $(n-1)$ and $1\leq p_j\leq(n-1)$.

We now write

$\hat{X}_1\left(t_{(n+1)j}\right)=\hat{X}_1\left(t_{nj}\right)\left\{T_{1\{p_j\to(p_j+1)\}}(j,j)\right\}$ where [5]

$$T_{1\{p_j\to(p_j+1)\}}(j,j)=\frac{\hat{X}_1\left(t_{(p_j+1)j}\right)}{\hat{X}_1\left(t_{(p_j)j}\right)} \quad [6]$$

Model 3

Consider a Dynamical State System denoted by $\overline{X}_1(t_i)$ for which we know the data for $i=1$ to n.

$\overline{X}_1(t_i)$ is a Row Vector with m Number of Elements wherein each element denotes the Value taken by the respective Parameter (among the m Parameters) of concern as i goes from 1 to n.

We denote the j^{th} element of $\overline{X}_1(t_i)$ as $X_1\left(t_{ij}\right)$ where $1\leq j\leq m$

We Normalize (Simple Vector Normalization) all State Vectors $\overline{X}_1(t_i)$ where $1 \leq j \leq m$ and $1 \leq i \leq n$ and represent them by $\hat{X}_1(t_i)$

We define $T_{1\{i \to (i+1)\}}$ as an $m \times m$ Square Matrix where all its diagonal elements are given by

$$T_{1\{i \to (i+1)\}}(j,j) = \frac{\hat{X}_1\left(t_{(i+1)j}\right)}{\hat{X}_1\left(t_{ij}\right)}$$

And all the off diagonal elements of $T_{1\{i \to (i+1)\}}$ are zero.

We now write

$$\left\{\hat{X}_1(t_n)\right\} = \sum_{b=1}^{(n-1)} \alpha_b \hat{X}_1(t_b) \qquad [7]$$

Now, equating the components of the same basis we get

$$\left\{\hat{X}_1\left(t_{nj}\right)\right\} = \sum_{b=1}^{(n-1)} \alpha_b \hat{X}_1\left(t_{bj}\right) \qquad [8]$$

and since $1 \leq j \leq m$, this equation is in fact m Number of Equations for $j = 1 \; to \; m$

If $m = (n-1)$, we solve for all the α_b for $b = 1 \; to \; (n-1)$.

If $m << (n-1)$, we can arbitrarily pick $(n-1-m)$ number of values of α_b and solve the rest of the m number of values of α_b using the aforementioned m Number of Equations.

Therefore, we can now write

$$\hat{X}_1\left(t_{(n+1)}\right) = \sum_{b=1}^{(n-1)} \alpha_b \left\{\hat{X}(t_b)\right\}\left\{\hat{T}_{\{b \to (b+1)\}}\right\} \qquad [9]$$

Prediction of the Magnitude of the Dynamic State Vector $\overline{X}_1\left(t_{(n+1)}\right)$

Model 1

De-Normalization Of States

We say that

$$\left\{\overline{X}_1\left(t_{n+1}\right)\right\} = \sum_{b=1}^{n} \beta_b \overline{X}_1\left(t_b\right) \quad [10]$$

Now, the above equation is actually m Number of Equations, and we have n Number of variables β_b to compute.

Component wise, the above is

$$\left\{X_1\left(t_{(n+1)j}\right)\right\} = \sum_{b=1}^{n} \beta_b \overline{X}_1\left(t_{bj}\right) \quad [11]$$

We now also note that

$$\left\{\hat{X}_1\left(t_{n+1}\right)\right\} = \sum_{j=1}^{m} X_1\left(t_{(n+1)j}\right)\hat{e}_j$$

Hence, we can write

$$\left\{\hat{X}_1\left(t_{(n+1)j}\right)\right\} = \frac{\left\{\sum_{b=1}^{n} \beta_b \overline{X}_1\left(t_{bj}\right)\right\}}{\left\{\sum_{j=1}^{m}\left\{\sum_{b=1}^{n} \beta_b \overline{X}_1\left(t_{bj}\right)\right\}^2\right\}^{1/2}} \quad [12]$$

Now, the above equation is actually m Number of Equations, and we have n Number of variables β_b to compute.

We now arbitrarily pick $(n-m)$ Number of Variables of β_b and compute the rest m Number of Variables of β_b using the aforementioned m Number of Equations in 12, as the LHS of equation 12 is known.

Hence, now as all β_b can be known, $\overline{X}_1\left(t_{n+1}\right)$ can be computed.

However, we should note that this $\overline{X}(t_{n+1})$ has $(n-m)$ arbitrary values in it. In order to compute the Real less arbitrary $\overline{X}(t_{n+1})$, we need to first compute the magnitude using the relation

$$\left|\overline{X}(t_{n+1})\right| = \left\{\sum_{j=1}^{m}\left\{\overline{X}\left(t_{(n+1)_j}\right)\right\}^2\right\}^{1/2} \quad [12]\text{-}2$$

And then write the Real less arbitrary $\overline{X}(t_{n+1})$ as

$$\overline{X}(t_{n+1}) = \left|\overline{X}(t_{n+1})\right| \hat{X}(t_{n+1}) \quad [12]\text{-}3$$

Model 2

De-Normalization Of States

For Model 1, we have

$$\hat{X}_1\left(t_{(n+1)j}\right)=\hat{X}_1\left(t_{nj}\right)\left\{T_{1\{l\rightarrow(l+1)\}}(j,j)\right\}$$

$$\hat{X}_1\left(t_{(n+1)j}\right)=\hat{X}_1\left(t_{nj}\right)\left\{\frac{\hat{X}_1\left(t_{(l+1)j}\right)}{\hat{X}_1\left(t_{lj}\right)}\right\}$$

Therefore, we can write

$$X_1\left(t_{(n+1)j}\right)=\left\{\left|\overline{X}_1\left(t_n\right)\right|\hat{X}_1\left(t_{nj}\right)\right\}\left\{\frac{\left\{\left|\overline{X}_1\left(t_{(l+1)}\right)\right|\hat{X}_1\left(t_{(l+1)j}\right)\right\}}{\left|\overline{X}_1\left(t_l\right)\right|\hat{X}_1\left(t_{lj}\right)}\right\} \qquad [13]$$

with $\left|\overline{X}_1\left(t_{(n+1)}\right)\right|=\sum_{j=1}^{m}\left\{\left\{X_1\left(t_{(n+1)j}\right)\right\}^2\right\}^{1/2}$

Now, we can write

$$\overline{X}_1\left(t_{(n+1)}\right)=\left|\overline{X}_1\left(t_{(n+1)}\right)\right|\left\{\hat{X}_1\left(t_{(n+1)}\right)\right\}$$

For Model 2, we have

$$\hat{X}_1\left(t_{(n+1)j}\right)=\hat{X}_1\left(t_{nj}\right)\left\{T_{1\{p_j\rightarrow(p_j+1)\}}(j,j)\right\}$$

$$\hat{X}_1\left(t_{(n+1)j}\right)=\hat{X}_1\left(t_{nj}\right)\left\{\frac{\hat{X}_1\left(t_{(p_j+1)j}\right)}{\hat{X}_1\left(t_{(p_j)j}\right)}\right\}$$

$$X_1\left(t_{(n+1)j}\right)=\left\{\left|\overline{X}_1\left(t_n\right)\right|\hat{X}_1\left(t_{nj}\right)\right\}\left\{\frac{\left|\overline{X}_1\left(t_{(p_j+1)}\right)\right|\left\{\hat{X}_1\left(t_{(p_j+1)j}\right)\right\}}{\left|\overline{X}_1\left(t_{(p_j)}\right)\right|\left\{\hat{X}_1\left(t_{(p_j)j}\right)\right\}}\right\} \qquad [14]$$

Now, we can write $\left|\overline{X}_1\left(t_{(n+1)}\right)\right|=\sum_{j=1}^{m}\left\{\left\{X_1\left(t_{(n+1)j}\right)\right\}^2\right\}^{1/2}$

Now, we can write

$$\overline{X}_1\left(t_{(n+1)}\right)=\left|\overline{X}_1\left(t_{(n+1)}\right)\right|\left\{\hat{X}_1\left(t_{(n+1)}\right)\right\}$$

For Model 3, we have

$$\hat{X}_1\left(t_{(n+1)}\right)=\sum_{b=1}^{(n-1)}\alpha_b\left\{\hat{X}\left(t_b\right)\right\}\left\{\hat{T}_{\{b\to(b+1)\}}\right\}$$

$$\hat{X}_1\left(t_{(n+1)}\right)=\sum_{b=1}^{(n-1)}\alpha_b\left\{\hat{X}\left(t_b\right)\right\}\left\{\frac{\hat{X}_1\left(t_{(b+1)j}\right)}{\hat{X}_1\left(t_{bj}\right)}\right\}$$

$$\overline{X}_1\left(t_{(n+1)}\right)=\sum_{b=1}^{(n-1)}\alpha_b\left|\overline{X}\left(t_b\right)\right|\left\{\hat{X}\left(t_b\right)\right\}\left\{\frac{\left|\overline{X}_1\left(t_{(b+1)}\right)\right|\left\{\hat{X}_1\left(t_{(b+1)j}\right)\right\}}{\left|\overline{X}_1\left(t_b\right)\right|\left\{\hat{X}_1\left(t_{bj}\right)\right\}}\right\} \quad [15]$$

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