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One Step Forecasting Model {Advanced Model} Version 3

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Abstract

In this research investigation, the author has presented an Advanced Forecasting Model.

Theory

Given,

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

$$Y_{\{(k+1)\mapsto n\},\{1\mapsto k\}} = \left\{ \overbrace{y_{k+1}, y_{k+2}, \ldots\ldots, y_{n-1}, y_n}^{\{(k+1)\mapsto n\}}, \overbrace{y_1, y_2, y_3, \ldots\ldots y_k}^{\{1\mapsto k\}} \right\}$$

Now, $y_{k+1}, y_{k+2}, \ldots\ldots, y_{n-1}, y_n$ can be arranged among themselves (within their position bounds) in $(n-k)!$ ways and $y_1, y_2, y_3, \ldots\ldots y_k$ can be arranged among themselves (within their position bounds) in $k!$ ways. Hence, the Vector $Y_{\{(k+1)\mapsto n\},\{1\mapsto k\}}$ can be arranged in $\{(n-k)! \times k!\}$ number of ways.

$${}^{j}Y_{\{(k+1)\mapsto n\},\{1\mapsto k\}} = j^{th}\ arrangement\ of\ elements\ of\ Y_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\ among\ the \{(n-k)! \times k!\} arrangements$$

$$Y_{\{n\mapsto((k+1))\},\{1\mapsto k\}} = \left\{ \overbrace{y_n, y_{n-1}, \ldots\ldots, y_{k+2}, y_{k+1}}^{\{n\mapsto((k+1))\},\{1\mapsto k\}}, \overbrace{y_1, y_2, y_3, \ldots\ldots y_k}^{\{1\mapsto k\}} \right\}$$

$$\hat{Y}_{\{n\mapsto((k+1))\},\{1\mapsto k\}} = \frac{\left\{ \overbrace{y_n, y_{n-1}, \ldots\ldots, y_{k+2}, y_{k+1}}^{\{n\mapsto((k+1))\},\{1\mapsto k\}}, \overbrace{y_1, y_2, y_3, \ldots\ldots y_k}^{\{1\mapsto k\}} \right\}}{\left\{ \sum_{i=1}^{n} y_i^2 \right\}^{1/2}}$$

Now, $y_n, y_{n-1}, \ldots\ldots, y_{k+2}, y_{k+1}$ can be arranged among themselves (within their position bounds) in $(n-k)!$ ways and $y_1, y_2, y_3, \ldots\ldots y_k$ can be arranged among themselves (within their position bounds) in $k!$ ways. Hence, the Vector $Y_{\{(k+1)\mapsto n\},\{1\mapsto k\}}$ can be arranged in $\{(n-k)! \times k!\}$ number of ways.

$$^{j}Y_{\{n\mapsto((k+1))\},\{1\mapsto k\}} = j^{th}\ arrangement\ of\ elements\ of\ Y_{\{n\mapsto((k+1))\},\{1\mapsto k\}}\ among\ the \{(n-k)! \times k!\} arrangements$$

$$\hat{Y}_n = \frac{\{y_1, y_2, y_3, \ldots\ldots, y_{n-1}, y_n\}}{\left\{\sum_{i=1}^{n} y_i^2\right\}^{1/2}}$$

$$^{j}\hat{Y}_{1,(n-k)} = \frac{^{j}Y_{\{(k+1)\mapsto n\},\{1\mapsto k\}}}{\left\{\sum_{i=1}^{n} y_i^2\right\}^{1/2}}$$

$$Co\sin eSimilarity\left(\hat{Y}_n,\ ^{j}\hat{Y}_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\right) = Dot\Pr oduct\left(\hat{Y}_n,\ ^{j}\hat{Y}_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\right)$$

$$Co\sin eSimilarity\left(\hat{Y}_n,\ ^{j}\hat{Y}_{\{n\mapsto((k+1))\},\{1\mapsto k\}}\right) = Dot\Pr oduct\left(\hat{Y}_n,\ ^{j}\hat{Y}_{\{n\mapsto((k+1))\},\{1\mapsto k\}}\right)$$

Model 1

Case 1:

For finding y_{n+1}

$$y_{n+1} = \sum_{k=0}^{n-1} \left(\breve{\breve{\alpha}}_{n-k}\right)\left(y_{k+1}\right)$$

Case 2:

For finding y_{n+1}

$$y_{n+1} = \sum_{k=0}^{n-1} \left(\breve{\breve{\alpha}}_{n-k}\right)\left(y_{n-k}\right)$$

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Case 1:

For computation of ${}^{j}\alpha_{n-k}$

$$ {}^{j}\alpha_{n-k} = \frac{Co\sin eSimilarity\left(\hat{Y}_n,\ {}^{j}\hat{Y}_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\right)}{\left\{\sum_{k=0}^{n-1}\left\{Co\sin eSimilarity\left(\hat{Y}_n,\ {}^{j}\hat{Y}_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\right)\right\}^2\right\}^{1/2}} $$

Case 2:

For computation of ${}^{j}\alpha_{n-k}$

$$ {}^{j}\alpha_{n-k} = \frac{Co\sin eSimilarity\left(\hat{Y}_n,\ {}^{j}\hat{Y}_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\right)}{\sum_{k=0}^{n-1}\left\{Co\sin eSimilarity\left(\hat{Y}_n,\ {}^{j}\hat{Y}_{\{(k+1)\mapsto n\},\{1\mapsto k\}}\right)\right\}} $$

For Computation of $\breve{\alpha}_{n-k}$

Case 1:

For Computation of $\breve{\alpha}_{n-k}$

$$ \breve{\alpha}_{n-k} = \sum_{j=1}^{\{(n-k)!\times k!\}}\left\{\frac{{}^{j}\alpha_{n-k}}{\sum_{j=1}^{\{(n-k)!\times k!\}}{}^{j}\alpha_{n-k}}\right\}{}^{j}\alpha_{n-k} $$ Self-Weighted Mean

Case 2:

For Computation of $\breve{\alpha}_{n-k}$

$$ \breve{\alpha}_{n-k} = \sum_{j=1}^{\{(n-k)!\times k!\}}\left\{\frac{{}^{j}\alpha_{n-k}}{\left\{\sum_{j=1}^{\{(n-k)!\times k!\}}\left\{{}^{j}\alpha_{n-k}\right\}^2\right\}^{1/2}}\right\}{}^{j}\alpha_{n-k} $$ Normalized Weight

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Case 1:

For Computation of $\breve{\breve{\alpha}}_{n-k}$

$$\breve{\breve{\alpha}}_{n-k} = \left\{ \frac{\breve{\alpha}_{n-k}}{\sum_{k=0}^{n-1} \breve{\alpha}_{n-k}} \right\}$$

Case 2:

For Computation of $\breve{\breve{\alpha}}_{n-k}$

$$\breve{\breve{\alpha}}_{n-k} = \frac{\breve{\alpha}_{n-k}}{\left\{ \sum_{k=0}^{n-1} \left\{ \breve{\alpha}_{n-k} \right\}^2 \right\}^{1/2}}$$

Model 2

$$y_{n+1} = \sum_{k=0}^{n-1} \left(\breve{\breve{\alpha}}_{n-k} \right) \left(y_{n-k} \right)$$

Case 1:

For computation of ${}^{j}\alpha_{n-k}$

$$ {}^{j}\alpha_{n-k} = \frac{CosineSimilarity\left(\hat{Y}_n , \hat{Y}_{\{n \mapsto ((k+1))\}, \{1 \mapsto k\}} \right)}{\left\{ \sum_{k=0}^{n-1} \left\{ CosineSimilarity\left(\hat{Y}_n , \hat{Y}_{\{n \mapsto ((k+1))\}, \{1 \mapsto k\}} \right) \right\}^2 \right\}^{1/2}}$$

Case 2:

For computation of ${}^{j}\alpha_{n-k}$

$$ {}^{j}\alpha_{n-k} = \frac{CosineSimilarity\left(\hat{Y}_n , \hat{Y}_{\{n \mapsto ((k+1))\}, \{1 \mapsto k\}} \right)}{\sum_{k=0}^{n-1} \left\{ CosineSimilarity\left(\hat{Y}_n , \hat{Y}_{\{n \mapsto ((k+1))\}, \{1 \mapsto k\}} \right) \right\}}$$

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For Computation of $\breve{\alpha}_{n-k}$

Case 1:

For Computation of $\breve{\alpha}_{n-k}$

$$\breve{\alpha}_{n-k} = \sum_{j=1}^{\{(n-k)!\times k!\}} \left\{ \frac{{}^{j}\alpha_{n-k}}{\sum_{j=1}^{\{(n-k)!\times k!\}} {}^{j}\alpha_{n-k}} \right\} {}^{j}\alpha_{n-k}$$ **Self-Weighted Mean**

Case 2:

For Computation of $\breve{\alpha}_{n-k}$

$$\breve{\alpha}_{n-k} = \sum_{j=1}^{\{(n-k)!\times k!\}} \left\{ \frac{{}^{j}\alpha_{n-k}}{\left\{ \sum_{j=1}^{\{(n-k)!\times k!\}} \left\{ {}^{j}\alpha_{n-k} \right\}^{2} \right\}^{1/2}} \right\} {}^{j}\alpha_{n-k}$$ **Normalized Weight**

For Computation of $\breve{\breve{\alpha}}_{n-k}$

Case 1:

For Computation of $\breve{\breve{\alpha}}_{n-k}$

$$\breve{\breve{\alpha}}_{n-k} = \left\{ \frac{\breve{\alpha}_{n-k}}{\sum_{k=0}^{n-1} \breve{\alpha}_{n-k}} \right\}$$

Case 2:

For Computation of $\breve{\breve{\alpha}}_{n-k}$

$$\breve{\breve{\alpha}}_{n-k} = \frac{\breve{\alpha}_{n-k}}{\left\{ \sum_{k=0}^{n-1} \left\{ \breve{\alpha}_{n-k} \right\}^{2} \right\}^{1/2}}$$

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