

## One Step Forecasting Model

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### Abstract

In this research investigation, the author has presented two models of One Step Forecasting.

### Theory

Given,

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

$$Y_{(k+1),n} = \{y_k, y_{k+1}, y_{k+2}, \dots, y_{n-1}, y_n\}$$

$$Y_{1,(n-k)} = \{y_1, y_2, y_3, \dots, y_{n-k-1}, y_{n-k}\}$$

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

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

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

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

*Cosin eSimilarity*( $\hat{Y}_{(k+1),n}$ ,  ${}^j \hat{Y}_{1,(n-k)}$ ) = *Dot Product*( $\hat{Y}_{(k+1),n}$ ,  ${}^j \hat{Y}_{1,(n-k)}$ )

**Model 1**

$$y_{n+1} = \sum_{k=0}^{n-1} (\alpha_{n-k}) (y_{n-k})$$

Case 1:

$$\alpha_{n-k} = \frac{\text{Cosine Similarity}(\hat{Y}_{(k+1),n}, \hat{Y}_{1,(n-k)})}{\left\{ \sum_{k=0}^{n-1} \left\{ \text{Cosine Similarity}(\hat{Y}_{(k+1),n}, \hat{Y}_{1,(n-k)}) \right\}^2 \right\}^{1/2}}$$

Case 2 :

$$\alpha_{n-k} = \frac{\text{Cosine Similarity}(\hat{Y}_{(k+1),n}, \hat{Y}_{1,(n-k)})}{\sum_{k=0}^{n-1} \left\{ \text{Cosine Similarity}(\hat{Y}_{(k+1),n}, \hat{Y}_{1,(n-k)}) \right\}}$$

**Model 2**

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

Case 1:

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

Case 2:

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

Case 1:

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

Case 2:

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

Case 1:

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

Case 2:

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

*Note:*

CosineSimilarity of only two different numbers can be taken as

1. Zero, i.e., 0
2. The Smaller Number among the two Numbers

Normalized CosineSimilarity of only two different numbers can be taken as

3. Zero, i.e., 0
4. Ratio of the Smaller Number by the Larger Number

## Results

### Model 1

For Model 1, when the first 8 Primes Numbers, i.e.,  $Y_n = \{2, 3, 5, 7, 11, 13, 17, 19\}$  were taken to predict the next Number, a result of 22.8606 was found. The next Prime Number being 23, the Error % was (23-22.8606)

$$\text{Error \%} = \left\{ \frac{(23 - 22.8606)}{23} \right\} \times 100 = 0.606087\%$$

## References

1. [http://www.vixra.org/author/ramesh\\_chandra\\_bagadi](http://www.vixra.org/author/ramesh_chandra_bagadi)
2. <http://www.philica.com/advancedsearch.php?author=12897>