EVALUATION OF THEILS U: A NAÏVE FORECAST APPLICATION

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Abstract. The reliability of any forecast needs to be tested effectively with an empirical data. Simple or complicated forecast methods have many a time failed subjected to empirical examination. There is no agreement among scholars as to which metric is the best for determining the best forecasting method. So this paper evaluates the basic of forecast techniques of predicting the future values and comparing its accuracy by Theil's U statistic. The predicted values were estimated by Naïve's method and the errors are calculated to verify the accuracy of the forecasted values as well. The testing has been done with a set of fictitious data set which helps to explain the steps in establishing the accuracy of the projected model.
Keywords: *forecast, Naïve, accuracy, error, Theil's U*

Introduction

Time series is a set of data collected in continuity order over successful equal increase of time (Hyndman and Koehler, 2006). Chronological order of observation on a variable of interest, apply this method to utilize daily, weekly, monthly, annual data on any interval reporting data. Forecasting is a prediction of future values of variable based on known past values of the variable. Prime time series component, are four: trend, seasonal, cycle, and irregular fluctuations. Trend is an upward or downward movement in its period time, seasonal variations are periodic pattern in time series that complete within year and repetitively, Cycle is an up and down movement around trend levels and Irregular fluctuations are movement in time series that no recognizable or non-regular pattern. Cycle fluctuations can have duration from two years to ten years (Hyndman and Athanasopoulos, 2013) whereas irregular fluctuations are caused by errors on part of time series analyst, unusual events that are unable to forecast. Forecast can, be based on expert judgments that are based on historical data and experiences (Green and Armstrong, 2015). Forecasting comprises of two types: quantitative technique and qualitative technique. Mathematically various forecast models can use different data and solve equations with myriad techniques. Methodically various forecast models can be created for the same data set using different methodologies to meet the same objective. As a result, the models differ in terms of resolution, output display, and how physical processes are integrated into them. Across applications a forecasting technique's role is legitimate if it fits the function and environment in context. Cross validation (accuracy measure) of forecast model is conducted with comparison approach used to verify the accuracy and relative efficiency of any researched model.

A quantitative technique on forecasting that used to collect historical data, formally summarizes patterns in data and express statistical relationship between previous and current values of variables to be projected in the data into the future (Brockwell and Davis, 2016). One of the techniques is Time Series forecast model accuracy metrics look at how accurate a model is within itself, i.e. how near the forecast values are to the observed values. In addition to predict the future estimates for action, forecast must be partnered with forecast accuracy measures (Siraj-Ud-Doulah, 2019). The desire for an accurate prognosis is self-evident. The selection of a forecast method is to extent dependent on the accuracy measurements (Chen and Leung, 2003). There are no equivalent conclusions in the accuracy measurement area. Myriad suggestions on accuracy measures from prior studies are inconclusive (Ribeiro et al., 2019). Therefore, what accuracy measures should be applied and its association with various features is needed. Because accuracy is the criterion that determines the best forecasting approach, it is the most significant factor to consider when assessing the quality of a forecast. The forecasts' purpose is to reduce error as much as possible.

Materials and Methods

Naïve forecast

The naïve prediction is one of the most basic forecasting approaches, and it is frequently used as a benchmark against which other approaches are measured (Akpinar and Yumuşak, 2017). It simply takes the most recent value of the variable in question and extrapolates the future value. Using a combination of naive forecasting models instead of just one simple equation, shows promise in boosting predicting accuracy at an acceptable additional cost (Russell and Adam Jr, 1987). Extrapolation approaches may be suitable for short-term forecast control projections of products or events with a lengthy history of stable demand (Armstrong, 2001). Naïve forecast method being one of the simplest techniques to estimate the predicted output is predominantly an effective threshold to differentiate different forecast models. The basic forecasting notation are Eq. (1);

$$e_t = (Y_t - \hat{Y}_{t+1}) \qquad \text{Eq. (1)}$$

Where, Y_t = value of time series at period t; $\hat{Y}_{t+1}$ = forecast value for Y_t; and e_t = residual or forecast error. The performance metrics of accuracy are all computed relative to naive estimates, which can be (1) Mean Absolute Error (MAE); (2) Mean Absolute Percentage Error (MAPE); (3) Mean Square Error (MSE); and (4) Root Mean Square Error (RMSE).

Mean Absolute Error (MAE)

MAE is used to measure forecast error in the same units as the original series.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \qquad \text{Eq. (2)}$$

Mean Absolute Percentage Error (MAPE)

MAPE is used to compute by finding the absolute error in each period, by dividing this actual observed value for that period and then average these absolute percentage errors.

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$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|Y_t - \hat{Y}_t\right|}{Y_t} \text{ x } 100\% \qquad \text{Eq. (3)}$$

Mean Square Error (MSE)

In mean square error method, each error or residual is squared and then summed and finally divided by the number of observations.

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2 \qquad \text{Eq. (4)}$$

Root Mean Square Error (RMSE)

Root mean square error is the square of mean square error (MSE), which is relatively measures can only be calculated when numerous forecasts on the same series are available, therefore they can't be used to assess out-of-sample forecast accuracy across a single forecast horizon

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \qquad \text{Eq. (5)}$$

Results and Discussion

Theil's U inequality

Theil's U threshold to compare the accuracy of a forecast model with a naive model, as stated below:

$$U = \frac{\text{RMSE forecast model}}{\text{RMSE naive model}} \qquad \text{Eq. (6)}$$

Where, U=1, the naive approach is as good as the forecasting technique being evaluated; U >1, there is no reason to use a formal forecasting method, since using a naïve method will generate better results; and U < 1, the forecasting technique being used is better than the naive approach.

Theil's U-statistic allows for a direct comparison of forecasting values to naive ones. Naive models are used to make comparisons against which the performance of more advanced methods is assessed (*Table 1*). The U-statistic is calculated as the ratio of a forecasting method's RMSE to the RMSE of a naive method's RMSE. If compared to the naive method, the smaller the U-statistic, the better the forecasting strategy (*Table 2*). The approach is preferable if the U-statistic is close to zero.

Table 1. *Hypothetical dataset with naïve estimates.*

Year	t	Yt	Ŷt
1996	1	926	-
1997	2	1171	926
1998	3	1663	1171

1999	4	2058	1663
2000	5	1892	2058
2001	6	1866	1892
2002	7	1414	1866
2003	8	1064	1414
2004	9	633	1064
2005	10	540	633

***Table 2**. Calculations for measures of accuracy.*

Time (t)	Yt	$\hat{Y}$t	et	|et|	et^2	|et| ÷ Yt × 100%
2	1171	926	245	245	60,025	20.92%
3	1663	1171	492	492	242,064	29.58%
4	2058	1663	395	395	256025	19.19%
5	1892	2058	-166	166	27556	8.77%
6	1866	1892	-26	26	676	1.39%
7	1414	1866	-425	452	204304	31.97%
8	1064	1414	-347	347	120409	32.52%
9	633	1064	-434	434	188356	68.56%
10	540	633	-93	93	8649	17.22%
TOTAL				2650	1008064	229.95

The calculation is below:

MAE = 1/9 (2650) = 294.44
MAPE = 1/9 (229.95) = 25.55
MSE = 1/9 (1008064) = 112007.11

RMSE = $\sqrt{(1/9 \text{ X } 1008064)}$ = 334.67

Given an example if forecast model = 105.164. Then U = 105.164/334.67 = 0.3142; which means its 0.31. The U statistic value is 0.31 < 1, thus the forecast model is better than naive model.

Relative measures can only be calculated when numerous forecasts on the same series are available, therefore they can't be used to assess out-of-sample forecast accuracy across a single forecast horizon. These accuracy measures have several drawbacks. Outliers, for example, have an impact on RMSE. According to Armstrong and Collopy (2000) unless represented as a percentage, these metrics are not independent of the unit of measurement. The accuracy of a forecasted model evaluated with MSE and MAE may not be appropriate because there might be significant differences in the scale of observations between series, causing a series with huge values to dominate comparisons. Absolute errors can be tough to work and train on their own. If a forecast error is 100 units, the severity of the inaccuracy cannot be understood until the series level is also provided. For such situations unit-free measurements must be used, and the mean absolute percentage error (MAPE) is preferably the most commonly used of these. As the mean value does not provide a measure of the error variance, the mean should not be utilised on its own. Its value should (but is not always) be in the vicinity of zero. It should ideally be equal to zero. As is generally known, the mean will not tell us anything about the error dispersion. Prior academic studies oscillate around myriad accuracy measurement. Theil's U or coefficient of inequality has great potential with simple interpretation to assess forecast accuracy and holds meaningful information of the forecast model.

Conclusion

Time series method in forecasting is used to measure a variable of interest. In practice, apply this method to utilize daily, weekly, monthly, annual data on any interval reporting data (Real Statistics using Excel, 2021). Usually used in business such as to measure unit sales of production over time, total money for a company over time, and number of unemployed or employed over time. There are four components of time series of each components caused by each factors and it is analyzed to find errors in variable. The relative track record of forecasting compares the performance of several methodologies as measured by systematic, unbiased, and trustworthy methodologies. It has nothing to do with people's happiness with predicting systems that have been in use for a long time. In fact, basic procedures are generally as accurate as complex approaches are one of the most persistent and helpful discoveries from forecasting research. However, if domain knowledge is unavailable, rule-based forecasting may be an option. It is notable that popularity of a technique does not imply its efficacy. It gives very little information regarding the methods' performance and the settings in which they are utilised. Primarily, forecasting systems allow us to compare alternate predictions, which improve accuracy. Thus, they can also be improved as we learn more about the problem.

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Conflict of interest

There are no conflict of interest involve with any parties in this research study.

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