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FORECASTING THE ECONOMIC CYCLES BASED ON AN EXTENSION OF THE HOLT-WINTERS MODEL. A GENETIC ALGORITHMS APPROACH

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Abstract: A key feature in fitting local polynomials and in using discounted least squares is the notion that the forecast should be "adaptive" in the sense that the low order polynomials used for extrapolations have coefficients that are modified with each observation. When the data exhibit seasonal behavior, several alternatives to ARIMA models exist. Here we focus on a direct extension of the Holt's model, due to Winters and often termed as the Holt-Winters model - which is available for nonstationary time series with seasonal components. The key problems in using this model are:
- the optimal choice of the parameters involved and for the initial steps;
- the optimal choice of the number of seasonal coefficients (especially when the data are not monthly or weekly recorded).

In this paper is proposed an alternative method based on a powerful searching technique - the Genetic Algorithms - for optimizing all the start-up parameters. Numerical examples of non-stationary time series with seasonal components complete the paper.

Keywords: time series forecasting, genetic algorithms.

I. Introduction

In the last years a great number of intelligent techniques - such as different types of Neural Networks (NN), Fuzzy Logic (FL) based algorithms, or the State Space Reconstruction method - promised insights that the traditional approaches to the very old problem of forecasting cannot provide.

By deriving the equivalence of the smoothing equation and the NN algorithm, [Ma] have proved that simple exponential smoothing is equivalent to a special type of NN. In [Pe] an approach based on fuzzy linear regression with fuzzy intervals for exponential smoothing was proposed; another interesting prediction method using FL (based on function approximation with fuzzy relations) is developed in [Ik].

The most difficult situation appears when the length of the time series is too short: in this case one can apply neither the traditional statistical procedures for parameter estimation, nor the NN algorithms. We propose in this paper a Genetic Algorithm method for finding the optimal parameters involved in the Holt-Winters model.

Genetic Algorithms (GA) are probabilistic search algorithms which start with an initial population of likely problem solutions and then evolve towards better solutions. Based on the mechanics of natural genetics and natural selection, GA combine survival of the fittest among string structures (called chromosomes) with a structured yet randomized information exchange to form a robust search algorithm, [Go].

A simple GA requires the definition of the following components: a genetic representation of the potential problem solutions (called "chromosomes"), a function verifying the fitness of the solution (called "objective function", or "fitness function") and the genetic operators of selection, mutation and crossover.

We analyze the efficiency of the GA method proposed on four examples (the first is a classical one from [Bo], and the others are real-world) of short-length, non-stationary time series with seasonal components. Each time series was shared in two parts: a training set and a test set (as in the NN methods). Some other experimental results are still in work.
II. The Holt-Winters seasonal model

The exponential smoothing forecasting procedure may be extended in order to incorporate the local linear trend and the seasonal component.

Non-stationary time series with seasonal components are usually fitted with local polynomials. The main idea is that the forecasts have to be adaptive, thus the low-order polynomials used for extrapolation must have different coefficients at each observation, [Ke]. Holt took this idea a step further by suggesting a forecasting function of the form:

$$F(t+k)=a_0(t)+ka_1(t)$$

where $a_0(t), i=1,2$ are updated according to the following recursive relations:

$$a_0(t)=\alpha_0y(t)+(1-\alpha_0)[a_0(t-1)+a_1(t-1)]$$
$$a_1(t)=\alpha_1[a_0(t)-a_0(t-1)]+(1-\alpha_1)a_1(t-1)$$

where $y(t), t=1,n$ corresponds to the real data available (from the training set). The values of $\alpha_0, \alpha_1, \alpha_2(1)$ and $a_1(1)$ are required to start.

When the data exhibit the seasonal behavior the direct extension of the Holt's method - proposed by Winters - may be applied. Thus, the forecasting function becomes:

$$F(t+k)=a_0(t)+ka_1(t)|C(t+k-s)$$

where $C(t)$ is a multiplication seasonal effect and "s" is the number of observation points in the whole year (e.g. 12 for the monthly data). The corresponding updating formulae are as follows:

$$a_0(t)=\alpha_0y(t)|C(s-t)+(1-\alpha_0)[a_0(t-1)+a_1(t-1)]$$
$$a_1(t)=\alpha_1[a_0(t)-a_0(t-1)]+(1-\alpha_1)a_1(t-1)$$
$$C(t)=\alpha_2y(t)|a_0(t)+(1-\alpha_2)C(t-s)$$

As in the two-parameters model, the values of $\alpha_0, \alpha_1, \alpha_2$, and the initial values of $a_0, a_1$ and $C$ are required at start. But if we look closely at the third equation we notice that we need to fix $s$ and find the best choice for the initial values $C(1), \ldots, C(s)$.

In the case of the first two examples we propose the use of a GA for optimizing the start-up parameters with the length of the seasonal component (cycle) apriori fixed (s=4, res. s=12).

In the last examples we extend the use of GA to the optimal choice of $s$ (and the corresponding initial values $C(1), \ldots, C(s)$). We point out the fact that these time series were recorded yearly, hence no seasonal characteristic could be apriori assumed.

III. Experimental results

The GA proposed for parameter estimation in the time series forecasting model is a canonical one, as in [Ag].

As the forecasting task presented in this paper did not require a great precision for the parameters and the start-up values we used a binary GA, not a real-valued one. The chromosome consists of more building blocks, corresponding to the values of $\alpha_0, \alpha_1, \alpha_2, \alpha_3$, $a_1(4), a_1(1), C(2), C(1), C(s)$ - for the Holt-Winters model with s=4, (and respectively to $\alpha_0, \alpha_1, \alpha_2, \alpha_3$, $a_1(12), a_1(12), C(1), C(2), C(3), \ldots, C(12)$ - for the Holt-Winters model with s=12), and to $s$, $\alpha_0, \alpha_1, \alpha_2, \alpha_3$, $a_1(s), a_1(s), C(1), \ldots, C(s)$ - for the Holt-Winters model with variable s.

The evaluation function is, as usual (see [Ke]), the forecasting mean square error (MSE): $E=(1/n)\sum_{i=1}^{n}(y(i)-F(i))^2$, where $y(i)$ are the desired values, $F(i)$ are the forecasting values and "n" is the number of training observations.

In fig.1 is depicted a classical example, from [Bo], fitted with the Holt-Winters seasonal model (s=12). The $\alpha$-values obtained by the GA are: $\alpha_0=0.94$, $\alpha_2=0.02$ and $\alpha_3=0.46$; the corresponding error $E=0.24$.

**Fig.1. A classical example (Box & Jenkins)**

![Forecast and Data](image-url)
In fig. 2 is represented a concrete example from an Airlines company, with data corresponding to the year 1995. This example was also fitted with the Holt-Winters model \((s=4)\). The obtained values of the parameters are as follows: \(\alpha_1=0.98\), \(\alpha_2=0.06\) and \(\alpha_3=0.40\); \(E=20.12\).

The following figures illustrate two time series predicted with an extension of the Holt-Winters model, namely considering the seasonal component (cycle length) \(s\) - variable. In fig.3 is presented the evolution of a GDP index; the best cycle length found by the GA on this problem was \(s_1=6\). In fig.4 is depicted the agricultural component of the same GDP; the best forecast corresponds to \(s_2=5\). We stress that the two cycle lengths obtained are very close - this finding has an economic reason: in the particular GDP considered, the agricultural component is prevalent.
IV. Conclusions

When one deals with short-length, non-stationary time series with seasonal components, the statistical procedures or even the neural networks approach prove to be unsatisfactory. In this paper is proposed an alternative method, based on a powerful optimization technique - the Genetic Algorithms. We underline the great applicability of GA in such type of prediction tasks, especially when a large number of parameters is required. In this situation the potential for economic artificial life is quite considerable. There are also presented encouraging results of applying GA for characterizing the seasonal behavior of historical time series.

References


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