INFORMATION SYSTEM OF FORECASTING BASED ON COMBINED MODELS WITH TIME SERIES CLUSTERING

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Abstract: *The article offers information system of time series forecasting based on the combined models of hybrid and selective types for various criteria of selection with the previous time series clustering by the methods of nearest neighbor and K - nearest neighbors.*

Keywords: *time series, combined forecasting model, information system, K-nearest neighbors' method.*

ACM Classification Keywords: *G.3 Probability and statistics - Time series analysis; H.4.2 Information Systems Applications: Types of Systems: Decision Support; H.1.1.Systems and Information Theory*

Introduction

The growth rate of national markets, trends of globalization, the complication of business relationships are some of the preconditions that today the development of economic systems takes place under uncertainty, instability and risk that is characterized by a significant degree of variability. In this regard, in unstable economic markets, the use of classical econometric statistical models and appropriate methods of time series forecasting, which reflect the financial and socio-economic indicators, is rather limited. Considerable part of the time series, for which forecasting problem appears, as a rule, is usually characterized by instability and non-stationary. Many easy-to-use forecasting models: exponential [Brown, 1959; Holt, 1957], linear regressive, autoregressive of ARIMA type [Box, 1976] are not intended to non-stationary time series forecasting, and those models that are appointed for this purpose, have some disadvantages, in particular, the model ARIMAX is characterized by the complexity of large number of parameters calculating and nonlinear regression model is limited by the problem of identifying functional relationships [Vercellis, 2009]. Complexity of forecasting process is also linked with the necessity to process and analyze large amounts of data. Therefore, today the state of forecasting methods development is closely related with the development of information technology. The so-called forecasting information systems that reflect this relationship within econometrics, financial mathematics, and statistics are used in the wide range of applied areas of science as well as in manufacturing, financial planning in economy and trade. Effective forecasting information systems can be used in decision-making, used by analysts to assess the risk of financial investments, etc.

Under the forecasting information system will consider interrelated totality of programs, each of which carries out a specific function: incoming information receiving, its maintenance and processing, forming of input data based on defined algorithms for the forecast realization for the user purposes. The main components of time series forecasting are the database with information about the object of study, in this case, the retrospective time series data, which is continuously updated, forecasting models complex and methods for their quality assessing, which are grouped depending on the problem of forecasting. The operation of such a system should carry out in interactive mode with the user or person who makes a decision. This system should be characterized by the required accuracy, flexibility, time saving and betimes react on changes in the dynamics of economic processes.

Developing of effective time series forecasting information systems is an urgent task for both for theory and practice. In particular, this system can be used by analysts, investors and traders to solve problems of money management, investment, planning, and so on. The purpose of the study is to build an information system of time series forecasting based on combined forecasting models with the previous time series clustering by nearest neighbor method and K-nearest neighbors to solve forecasting problems of values and time series signs increments.

Problem Statement

Discrete time-series $\{z_i\}_{i=1}^{n} = \{z_1, z_2, \ldots, z_n\} = \{z(t_1), z(t_2), \ldots, z(t_n)\}$ will be called a finite sequence of values that are fixed at discrete time points $t_i \in S$, $i = \overline{1,n}$, S – some discrete set. We'll assume that the measurements are valid, are fixed at defined time points and are the economic or financial indexes.

There are major problems that can be solved within the framework of information systems: forecasting of time series values, increments signs forecasting, identifying of time series local extreme points. In this paper restrict ourselves to the first two. Formulate each of them separately.

Problem of time series values forecasting. Based on retrospective values z_n, z_{n-1}, z_{n-m+1}, $m \le n$ of series $\{z_i\}_{i=1}^{n}$, to estimate most accurately its behavior in future in moments $t_{n+1}, t_{n+2}, \ldots, t_{n+\theta}$ i.e. to build a sequence of forecasting values $\{\hat{z}_i\}_{i=n+1}^{n+\theta} = \{\hat{z}_{n+1}, \hat{z}_{n+2}, \ldots, \hat{z}_{n+\theta}\}$ where θ – the prediction horizon, and m – volume retrospective sample. Denote by $\hat{z}_\tau(n)$ – forecast, that is calculated at the time t_n (at the point n) for τ points forward. Forecast of time series values $\{z_i\}_{i=1}^{n}$ for one point forward can formally be written as $\hat{z}_{n+1} = \hat{z}_1(n) = f(z_{n-m+1}, z_{n-m+2}, \ldots, z_n)$, where f – forecasting model. In the case of forecasting with horizon $\theta > 1$ such approach can be used:

$$\hat{z}_{n+1} = \hat{z}_1(n) = f(z_{n-m+1}, z_{n-m+2}, \ldots, z_n),$$
$$\hat{z}_{n+2} = \hat{z}_2(n) = f(z_{n-m+2}, z_{n-m+3}, \ldots, z_n, \hat{z}_{n+1}),$$
$$\vdots$$
$$\hat{z}_{n+\theta} = \hat{z}_\theta(n) = f(z_{n-m+\theta}, \ldots, \hat{z}_{n+\theta-2}, \hat{z}_{n+\theta-1}),\ m \le n .$$

It should be noted that different forecasting models may have different mechanisms for calculating the forecasts; external factors, the various options that require separate assessment may be taken into account. To build the most accurate forecast means to build a model that meets the criteria for assessing the quality of prediction. For this problem the average absolute deviation, average square error, standard deviation, relative error and so on may be such criteria.

Problem of time series increments signs forecasting. Based on a $\{z_i\}_{i=1}^{n}$ build up the series, which consists of first differences $\{\Delta z_i\}_{i=1}^{n}$, where $\Delta z_i = z_i - z_{i-1}$, $i = \overline{2,n}$. Denote by $\{\chi_i\}_{i=2}^{n}$ signed series, where $\chi_i = \mathrm{sgn}(\Delta z_i)$. Sign increment forecast, which is calculated at the point n for τ points forward denote by $\hat{\chi}_\tau(n)$. Denote by F increment sign forecast model on one point forward. Then forecast can be formally written as: $\hat{\chi}_{n+1} = \hat{\chi}_1(n) = F(z_{n-m+1}, z_{n-m+2}, \ldots, z_n)$. Some quality criteria for the forecasting of this model, in particular that based on Heaviside function, are described in the work [Berzlev, 2013].

Consider the general formulations of values and time series signs increments forecasting problems. Problem statement of time series values forecasting is formulated as follows: let give the set of forecasting models $f_1, f_2, \ldots, f_N$, as the basis of which for a series $\{z_i\}_{i=1}^{n}$ in the point n the estimates of time series future elements can be built, $\{\hat{z}_{n+1}^{p}, \hat{z}_{n+2}^{p}, \ldots, \hat{z}_{n+\theta}^{p}\}$, $p = \overline{1,N}$, N – the number of forecasting models. Based on this models set and retrospective series $\{z_i\}_{i=n-m+1}^{n}$ at the point n to calculate the most accurate predictive values sequence $\hat{Z} = \{\hat{z}_i\}_{i=n+1}^{n+\theta} = \{\hat{z}_{n+1}, \hat{z}_{n+2}, \ldots, \hat{z}_{n+\theta}\}$.

Statement of increments signs forecasting problem is formulated as follows: let the set of increments signs forecasting models $F_1, F_2, \ldots, F_L$ is given, on the base of them in the point n of time series $\{z_i\}_{i=1}^{n}$ the estimates of increments signs can be calculated $\hat{\chi}_1^p(n)$, $p = \overline{1, L}$, L – the number of increments signs forecasting models. The based on a set of data models and retrospective series $\{z_i\}_{i=n-m+1}^{n}$ at a point n to calculate the most accurate predictive assessment of increment sign on one point forward.

The objective of this study is the development of such information system, which based on combined forecasting models with prior time series clustering in interactive mode with the user, defines forecast with the desired accuracy for the user's purposes. When combined we'll mean models that are based on a certain number of other models by hybridization or selection. When clustering for nearest neighbor method will understand the partitioning of time series into clusters of fixed length and location for the last specified cluster (which precedes the point where the forecast is calculated) based on proximity measure of similar to it cluster, distance to which is the minimal. The problem of such clusters finding is solved on the basis of K - nearest neighbors [Singh, 2000; Fernández-Rodríguez, 2002; Berzlev, 2013].

Development of information system forecasting

At the initial stage of information systems development problems, that should be solved, should be identified, the goals of systems building should be determined; methods for finding solutions should be defined, formalizing and structuring of knowledge occurs. The next step is the implementation of the system and its testing. Consider the key stages of the information system.

Step 1. The time series clustering by nearest neighbor or K - nearest neighbors methods. Do the length cluster m of the time series $\{z_i\}_{i=1}^{n}$ as the subsequence $\{z_{k_j}\}_{j=1}^{m}$ of m elements, $m < n$, $k_{j+1} = k_j + 1$ for $j = \overline{1, m-1}$ (the sequence order of elements in the subsequence is the same as in the time series). Clusters can be represented directly as the subsequences of the input time series elements, or by entering the distances between elements in the middle of the cluster.

In the case of increments signs forecast the clusters representations based on signed sequences are considered. If $\{\chi_i\}_{i=2}^{n}$ – signed sequence of the time series $\{z_i\}_{i=1}^{n}$, signed clusters will be:

$$\chi_{(m)}^s = \{\chi_{k_1^s}, \chi_{k_2^s}, \ldots, \chi_{k_m^s}\} = \{\chi_{k_j^s}\}_{j=1}^{m},\ k_{j+1}^s = k_j^s + 1,\ \chi_{k_1^s} = \chi_s,\ s = \overline{2, n-m},$$

where $\chi_{(m)}^s$ – cluster, that consists of m elements, s – initial element series index. Do the $\chi_{(m)}^{n-m+1}$ – pivotal cluster, in other words, last available cluster, the other ones $\chi_{(m)}^s$, $s = \overline{2, n-m}$ – non-pivotal clusters. It is evident that the number of non-pivotal cluster of m elements, that are building based on series of n elements is equal $n - m - 2$ [Berzlev, 2013].

In the case of time series values forecasting the clusters representations are considered directly on the time series elements:

$$z_{(m)}^s = \{z_{k_1^s}, z_{k_2^s}, \ldots, z_{k_m^s}\} = \{z_{k_j^s}\}_{j=1}^{m},\ k_{j+1}^s = k_j^s + 1,\ j = \overline{1, m-1},\ z_{k_1^s} = z_s .$$

The cluster $z_{(m)}^{n-m+1}$ is called the pivotal cluster, all other clusters are called non-pivotal clusters $z_{(m)}^s$, $s = \overline{1, n-m}$.

The set of all non-pivotal clusters denote as $\Re$. It should be noted that in [Singh, 2000] the term pattern is used for the term cluster. In paper [Fernández-Rodríguez, 2002] the term vector is used, also different authors use such terms as set, pieces, etc.

Since each cluster can be represented by a point in m - dimensional space, it is possible to calculate the proximity measure or metric distances between the pivotal cluster and all non-pivotal clusters. As proximity measures it can be used: Euclidean, Minkowsky, Mahalanobis distances, or in the case of cluster-based representation of sign sequences: Hamming similarity, Rogers-Tanimoto measure, etc. As the result of clustering algorithm application by K- nearest neighbors' method, the non-pivotal clusters, similar to the pivotal cluster (the distance of which to the pivotal cluster is minimal) will be received.

Step 2. Since the forecasting accuracy determines not only by forecasting models possibilities, but also by forecasting objects characteristics, i.e. time series on which these models are implemented, the key steps are the time series preprocessing and analysis of its structure.

Step 3. Formation of the general set of forecasting models. On the next step for the problem of time series values forecasting the general set $\Im_{PS}$ of forecasting models $f_1, f_2, \ldots, f_N$, which can consist as from different classes models and so as from identical models but with different sets of parameters, is formulated.

Polynomial models with adaptive parameters: Brown, Trigg-Leach, Holt, Winters adaptive polynomial models, etc, [Berzlev, 2011; Berzlev, 2012] are recommended to include to the set. For the increments signs forecasting problem the set of specific models $F_1, F_2, \ldots, F_L$ is formed. To this type of models moving averages models can be included. In particular, the paper [Berzlev, 2013] proposes to choose the following indicators:

$\chi_1(n) = \mathrm{sign}\left(\frac{1}{p}\sum_{i=1}^{p} z_{n-i+1}\right)$ – increment sign forecasting based on simple moving average with $p > 0$ period;

$$\chi_1(n) = \mathrm{sign}\left(\frac{1}{\nu_p}\sum_{i=1}^{p}(p-i+1)z_{n-i+1}\right),\ \nu_p = \sum_{i=1}^{p} i \text{ – weighted moving average;}$$

$$\chi_1(n) = \mathrm{sign}\left(\sqrt[p]{\prod_{i=1}^{p} z_{n-i+1}}\right) \text{ – geometric moving average;}$$

$$\chi_1(n) = \mathrm{sign}\left(\prod_{i=1}^{p}(z_{n-i+1})^{p-i+1}\right)^{\frac{1}{\nu_p}},\ \nu_p = \sum_{i=1}^{p} i \text{ – weighted geometric moving average.}$$

Step 4. Identification and adaptation of models. Let to the general sets of models adaptive polynomial models of Brown, Trigg-Leach, Holt, Winters, each of which has a number of parameters that need to adapt in each time series point, in which the prognosis is implemented, were included. Time series is divided into two sections: experimental and predicted, on each of them the forecast by models from the general set $\Im_{PS}$ is implemented. Experimental section, in turn, is divided into two parts, the model parameters adaptation, which allows eliminating of the impact of the initial parameters choice on the forecasts results that are implemented in the second part of the experimental plot of the series, takes place on the first of them. We'll also assume that the mechanism of models adaptation from the general set of parameters $\Im_{PS}$ by the refinement of at each point of the input series according to the forecasts errors in the previous steps, were assigned. Note that the initial parameters of the models are given a priori, based on the structure of the time series and the specific characteristics of each forecasting model or are calculated on the experimental time series interval.

Step 5. The forecast implementation for each of the models, which are the components of an information system, depending on the user's purpose. Consider for example two models for each of the prediction tasks set out above.

Adaptive combined forecasting model of selective and hybrid types with previous clustering by nearest neighbor method.

Selective approach is the selection for each value τ at each point of time series from programming set $\Im_{PS}$ of a single model, that provides highly accurate forecasting for a particular selection criterion: B-criterion [Lukashin, 2003], R-criterion [Berzlev, 2012] on the current site time series. Parameters selection criteria usually have an adaptive character. Also, often, to improve the accuracy of forecasting, the selection criteria do not apply to the program, but to the so-called basic set $\Im_{BS}^{\tau}$. It is a subset of the basic set consisting of such models, which give the most accurate predictions for the current site time series. The selection of models to the basic set can be done, for example, based on the D-criterion [Lukashin, 2003]. Forecast for the hybrid approach is calculated as the weighted sum of forecasts by all models that make up the basic set $\Im_{BS}^{\tau}$. Build up a forecast based on these approaches, using the results of the time series clustering (step 1).

Selective method. Let the series clustering by nearest neighbor method was conducted i. e. based on certain proximity measure, such as Euclidean distance, the cluster $z_{(m)}^{x-m+1} \in \Re$ was defined, which is most similar to the pivotal cluster $z_{(m)}^{n-m+1}$. The last element of the cluster $z_{(m)}^{x-m+1}$ will be an element z_x, the last element of the cluster $z_{(m)}^{n-m+1}$ will be an element z_n.

For each fixed τ do a basic set of forecasting models $\Im_{BS}^{\tau}$ using D-criterion. D-criterion value at the time t_x can be calculated by the formula:

$$D_p(\tau) = \frac{1}{x-c+1} \sum_{j=0}^{x-c} \left(\hat{z}_{\tau}^{p}\left(x-\tau-j\right) - z_{x-j} \right)^2,$$

where τ – the forecast period, c – prehistory period, $\hat{z}_{\tau}^{p}\left(x-\tau-j\right)$ – the forecast, which is calculated at the moment $t_{x-\tau-j}$ (в точці $x-\tau-j$) for τ steps forward by model f_p, $p=\overline{1,N}$. Then the basic set of models for fixed τ is defined as:

$$\Im_{BS}^{\tau} = \left\{ f_p \in \Im_{PS} \middle| D_p\left(\tau\right) \le \lambda\, D_{\min}\left(\tau\right), p=\overline{1,N} \right\},\ D_{\min}(\tau) = \min_{p=\overline{1,N}} D_p(\tau),$$

where $\lambda \in \mathbb{R}$ – selection parameter, in practice it is recommended to choose $\lambda \in [1.2, 1.5]$.

Denote the models that have been included into the set $\Im_{BS}^{\tau}$ by $f_1^{\tau}, f_2^{\tau}, \ldots, f_{L_\tau}^{\tau}$, L_τ – the number of models in this set, $\tau = \overline{1,\theta}$, $L_\tau \le N$.

For each model in the basic sets $\Im_{BS}^{\tau}$ we calculate the value of the B-criterion:

$$B_{x,\tau}^{q_\tau} = (1-\alpha_B) B_{x-1,\tau}^{q_\tau} + \alpha_B e_{\tau}^{q_\tau}(x-\tau), \tag{1}$$

where $0 < \alpha_B \le 1$ – the smoothing parameter, and $e_{\tau}^{q_\tau}\left(x-\tau\right) = \left| \hat{z}_{\tau}^{q_\tau}\left(x-\tau\right) - z_x \right|$ – the absolute forecast error, which is calculated at the moment $t_{x-\tau}$ for τ steps by models $f_{q_\tau}^{\tau}$, $\tau = \overline{1,\theta}$, $q_\tau = \overline{1, L_\tau}$. Then such a model f^{τ^*}, for which B-criterion minimum value is provided, would be considered as the most accurate model for fixed τ by B-criterion $\min\limits_{q_\tau=\overline{1,L_\tau}} \left\{B_{x,\tau}^{q_\tau}\right\}$. Forecast that is based on models f^{τ^*} at the point n on τ steps further denote as $\hat{z}_\tau^*(n)$. Then the forecast at a point n for combined model of selective type by the B- selection criterion (1) with time series clustering using nearest neighbor will be calculated by the formula:

$$\hat{z}_\tau(n) = \alpha\, \hat{z}_\tau^*(n) + (1-\alpha)\, z_{x+\tau}, \tag{2}$$

where $z_{x+\tau}$ – the time series value, which follows on τ points after $z_{(m)}^{x-m+1}$ cluster, similar to the pivotal cluster, $\alpha \in [0,1]$ – parameter which indicates the importance of taking into account the estimated values of selected model in forecast.

A hybrid method. Let after the clustering in point x for each τ the basic $\Im_{BS}^\tau$ sets were formed and values of B-criteria $B_{x,\tau}^{q_\tau}$ (1), $q_\tau = \overline{1,L_\tau}$ were calculated. Denote by $\hat{z}_\tau^{q_\tau}(n)$ the forecast, which is calculated at the point n on τ points forward for the $f_{q_\tau}^\tau$ models from the basic set $\Im_{BS}^\tau$, Then the forecast of combined model of hybrid type with clustering by nearest neighbor method is given as:

$$\hat{z}_\tau(n) = \alpha \sum_{q_\tau=1}^{L_\tau} \omega_\tau^{q_\tau}\, \hat{z}_\tau^{q_\tau}(n) + (1-\alpha)\, z_{x+\tau}, \tag{3}$$

where $\alpha \in [0,1]$, weights $\omega_\tau^{q_\tau}$ can be defined on the B-criterion (1) [Lukashin, 2003] taking into account the factor of proportionality, which is determined from the unity weights sum equality, $\sum\limits_{q_\tau=1}^{L_\tau} \omega_\tau^{q_\tau} = 1$, i.e.

for $L_\tau = 2$ $\quad \omega_\tau^1 = \dfrac{B_{x,\tau}^2}{B_{x,\tau}^1 + B_{x,\tau}^2}$, $\omega_\tau^2 = \dfrac{B_{x,\tau}^1}{B_{x,\tau}^1 + B_{x,\tau}^2}$,

for $L_\tau = 3$ $\quad \omega_\tau^1 = \dfrac{B_{x,\tau}^2 B_{x,\tau}^3}{B_{x,\tau}^1 B_{x,\tau}^2 + B_{x,\tau}^1 B_{x,\tau}^3 + B_{x,\tau}^2 B_{x,\tau}^3}$, $\omega_\tau^2 = \dfrac{B_{x,\tau}^1 B_{x,\tau}^3}{B_{x,\tau}^1 B_{x,\tau}^2 + B_{x,\tau}^1 B_{x,\tau}^3 + B_{x,\tau}^2 B_{x,\tau}^3}$,

$$\omega_\tau^3 = \frac{B_{x,\tau}^1 B_{x,\tau}^2}{B_{x,\tau}^1 B_{x,\tau}^2 + B_{x,\tau}^1 B_{x,\tau}^3 + B_{x,\tau}^2 B_{x,\tau}^3},$$

and so on.

After the forecast calculating predicted point $\hat{z}_1(n)$ is used to build a new pivotal cluster $z_{(m)}^{n-m+2} = \{z_{k_1^{n-m+2}}, z_{k_2^{n-m+2}}, \ldots, z_{k_{m-1}^{n-m+2}}, \hat{z}_1(n)\}$, $z_{k_1^{n-m+2}} = z_{n-m+2}$, and the old pivotal cluster $z_{(m)}^{n-m+1}$ becomes non-pivotal cluster that is included to the set $\Re$, and the calculation process starts over again, that is based on certain proximity measure to the pivotal cluster, $\Im_{BS}^\tau$ sets are formed for each τ, the B-criterion value is calculated for each forecasting model that uses a similar non-pivotal cluster sequence as retrospective information. Further the forecast is built according to the selective or hybrid principles (1-3).

Signs increment forecasting model with the prior clustering by K-nearest neighbors' method.

Let on certain proximity measure basis in point z_n K clusters $\chi_{(m)}^{y-m+1} \in \aleph$, $y \in [m+1, n-1]$, $\mathrm{card}(\aleph) = K$, similar to the pivotal cluster $\chi_{(m)}^{n-m+1}$, were defined, $\aleph$ - clusters set, similar to the pivotal cluster. The last element of each clusters $\chi_{(m)}^{y-m+1}$ are the elements z_y. In this method we'll be limited to the selective principle of forecasting building. As the selection criterion in z_y points the assessment:

$$I = \frac{1}{m}\sum_{j=1}^{m}\gamma_j H_h\left(\hat{\chi}_1^p(y-j)\Delta z_{y-j}\right). \tag{4}$$

will be used, where γ_j - weights coefficients, $\sum_{j=1}^{m}\gamma_j = 1$, $H_h(x) = \begin{cases} 0, & x < 0 \\ h, & x = 0 \\ 1, & x > 0 \end{cases}$, $x \in \mathbb{R}$ – Heaviside function.

Differences Δz_{y-j}, $j = \overline{1,m}$ are build from clusters elements $\chi_{(m)}^{y-m+1} \in \aleph$, $p = \overline{1,L}$, [Berzlev, 2013]. To simplify in the points z_y we'll select a single model for which criterion I (4) is maximal. Denote the increments signs projections of selected models to one point forward, which are calculated in the points z_y (for each cluster) by $\chi_{1,d}^{*}(y)$, $d = \overline{1,K}$,. Then increment sign forecast to one point forward, which is calculated at point z_n can be defined by formula:

$$\chi_1(n) = \mathrm{sign}\left(\sum_{d=1}^{K} H_h(\chi_{1,d}^{*}(y)) - \frac{K}{2}\right) \tag{5}$$

Conclusions

Scientific novelty. The forecasting information system that is based on adaptive combined models of hybrid and selective types according to various criteria of selection, the previous time series clustering methods for nearest neighbor and K- nearest neighbors was described. Clustering options, proximity measure, and other models indicators can be defined by users in the course of the forecast. Information system solves two actual problems: time values series forecasting with determined predicted horizon and time series increments forecasting to one point forward.

The practical value. The described information system was realized in the software environment Delphi. A comparative analysis of time series forecasting of prices (petrol, silver, aluminum, data were selected for the last three years, total 700 measurements) using the conventional adaptive combine models based on adaptive polynomial models of Brown, Trigg-Leach etc. and combined models with the prior time series clustering was conducted. Results of the analysis suggest that the proposed an article models (1-3), which are the components of information system provide a higher accuracy in case of forecasting with period $\tau > 5$.

Signs increments forecasting model (4,5) also allows to improve forecasting accuracy compared with naive algorithm and the known series forecasting model with unstable nature of oscillations, as described in the [Lukashin, 2003]. Details of the model test and numerical results are shown in the paper [Berzlev, 2013].

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