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ANALIZA CZASOWA Z UWZGLĘDNIENIEM RÓŻNYCH POZIOMÓW INFORMACJI

Streszczenie: Jeśli stan obiektu nie zmienia się, modele predykcyjne są naprawdę przydatne do oceny stan. Jednak w dzisiejszych czasach jest to prawie niemożliwe, ponieważ stan obiektów nieustannie ewoluuje. Do rozwiązania tego problemu zastosowano filtr predykcyjny Kołmogorowa-Gabora. Tym, co odróżnia analizę szeregów czasowych od badań, jest to, że elementy szeregów czasowych mają swoją strukturę, która ewoluuje w czasie. Również modele szeregów czasowych często używają uporządkowania jednokierunkowego, co oznacza, że elementy szeregu czasowego uzyskane w tym okresie będą pochodzić z wcześniejszych elementów szeregu czasowego zgodnie z tym okresem.
Może istnieć wiele różnych form modeli dla danych szeregów czasowych. Główne trzy klasy o znaczeniu praktycznym to: modele autoregresyjne (AR), modele zintegrowane (I) i modele średniej ruchomej (MA).

Keywords: prognoza dla szeregów czasowych, model predykcji, struktura wewnętrzna

TIMELINE ANALYSIS WITH DIFFERENT INFORMATION LEVELS

Summary: If the condition of the object does not change in the future, prediction models are really useful. However, nowadays it is almost impossible, because objects state is continually accelerating. The Kolmogorov-Gabor prediction filter was used to solve this problem.
What makes the analysis of the time series different from the average studies is that the elements of the time series have their structure that has changed over time. Also time series models often use one-way ordering which means that the elements of the time series obtained during this period will be derived from the earlier elements of the time series according to this period.
There can be many different forms of models for given time series. The main three classes of practical importance are: autoregressive (AR) models, integrated (I) models, and moving average (MA) models.

Keywords: time series forecast, model prediction, internal structure

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These objects of study are complex systems, that is, those for which adequate information needs to be used so far inaccessible information. The complexity of an object is reduced by its decomposition at the level of information transformation. The level of information transformation is a set of local information transformation tasks. The level of information transformation is a set of local information transformation tasks. This article is aimed to determine the methods of decomposing the process of modeling complex systems and find a proper way of developing monitoring intelligent systems to forecast basically any currency rate.

1. Time series forecasting

The element of the time series is the numerical value of the object's characteristics. Time series elements are obtained while monitoring industrial processes or tracking corporate business metrics. Informative means the ability of a row element accurately to display the properties of an object at a particular observation point. The elements of the series are used by predictive model synthesis algorithms (PMSAs). Reliable display of the properties of the object at discrete intervals allows PMSA to build a forecasting model with a long forecasting horizon. Time series forecasting is the use of a model to predict the numerical values of an characteristic of object based on previously observed values [1].

Different informativeness of the elements of the time series is caused by the change of the state of the object which characteristics are predicted, perturbations of external and internal, registration of the numerical characteristics of the object by different technical means having different indicators of accuracy of measurements, and other reasons [2].

Prediction models are useful if the condition of the object does not change in the future. Nowadays, the changing state of objects is continually accelerating. Therefore, the task is to determine the state of the object, using a predictive model based on the elements of the time series of different informative.

The Kolmogorov-Gabor`s prediction filter was used to investigate the use of time series with variable informativeness of elements in this work [3]. It is an analog or digital device, at the input of which both the value of the function of interest and the values of the corresponding variables (correlated) are given. Both the valuesof the variables at the moment and their value at any point in the prehistory are used.

The next value of a predicted function is derived from the values of that function in the past. The sampling rate of the function under study is constant.

The elements of the time series have their structure that has changed over time. This makes the analysis of the time series with elements of different informative content different from the average studies, which do not have a natural ordering of observations. Analyzing such a time series is also different from analyzing spatial data, where observations are typically geographic (such as location-based house prices, as well as the internal characteristics of buildings). The stochastic time series model confirms the fact that observations approximated in time are not always more closely related than earlier observations. For example, when you change the status of a monitoring object, such as switching to crisis monitoring, a predictive model built on the elements of the time series fixed in the normal mode will lose their usefulness.

In addition, time series models often use one-way ordering. Therefore, the elements of the time series obtained during this period will be derived from the earlier elements of the time series according to this period.

In statistics, forecasting is part of the statistical conclusion. One specific approach to such a conclusion is known as a predictive conclusion, but a forecast can be taken as part of any of several approaches to a statistical conclusion. Indeed, one description of statistics is that it provides a means of transferring knowledge about a sample of the population of the entire population and other related groups of the population, which does not necessarily coincide with the forecast in time. When information is transmitted over time, often at specific points in time, this process is called forecasting [1].

Fully-formed statistical models for stochastic modeling purposes to generate alternative versions of time series representing what could happen over an indefinite period of time in the future

Simple or fully formed statistical models for describing the likely results of time series in the near future, taking into account knowledge of the most recent results (forecasting).

Time series forecasting is usually performed using automated statistical software packages and programming languages such as Apache Spark, Julia, Python, R, SAS, SPSS and many others.

Large-scale data prediction is performed using Spark, which has the spark-ts package as a third-party package.

2. Estimating the change of the object

Dependences of the number of correctly predicted characteristics of the process dynamics on the number of steps of the model forecast horizon at a given time are revealed [2].

The peculiarities of using the model prediction results based on the Kolmogorov-Gabor`s filter in the process of estimating the change of the object state in order to identify the point after which the use of the prediction model based on historical data loses its relevance.

It is suggested to evaluate the accuracy of the prediction taking into account the change in the condition of the projected object.

Thus, to build predictive models based on a time series with elements of different informative nature, it is necessary to take into account the change of the object state, the internal structure of the time series, and to identify historical periods with similar properties of the elements of the time series.

3. Time series analysis methods

Time series analysis methods can be divided into two classes: methods in the frequency domain and methods in the time domain. The first includes spectral analysis and wavelet analysis; the latter include autocorrelation and cross-correlation analysis. In the time domain, correlation and analysis can be performed in the form of a filter using scaled correlation, thereby reducing the need for work in the frequency domain.

In addition, time series analysis methods can be divided into parametric and nonparametric methods. Parametric approaches suggest that the underlying stationary random process has a definite structure that can be described using a small number of parameters (for example, using the autoregressive model or moving average). In these approaches, the challenge is to evaluate the parameters of a model that describes a random process. In contrast, nonparametric approaches explicitly evaluate the covariance or spectrum of a process, not assuming that the process has any particular structure [4].

Time series analysis methods can also be divided into linear and non-linear, as well as one-dimensional and multidimensional.

4. Models

Models for given time series can take many forms and represent various random processes. In modeling process level changes, three main classes of practical importance are used: autoregressive (AR) models, integrated (I) models, and moving average (MA) models. These three classes are linearly dependent on previous data points. Combinations of these ideas give the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. The fractional integrated moving average (ARFIMA) autoregressive model summarizes the first three. Extensions of these classes for working with vector-valued data are available under the heading of multidimensional time series models, and sometimes the previous abbreviations are expanded by including the initial “V” for the “vector”, as in VAR for vector autoregression. An additional set of extensions of these models is available for use in cases where the observed time series is due to a certain “forced” time series (which may not have a causal effect on the observed series): the difference from the multidimensional case is that the series of actions can be deterministic or be under the control of the experimenter. For these models, the abbreviations are deciphered with the final “X” for “exogenous” [1].

The nonlinear dependence of the level of a series on previous data points is of interest, in part because of the possibility of creating a chaotic time series. However, more importantly, empirical studies can show the advantage of using forecasts derived from non-linear models compared to linear models, as, for example, in non-linear autoregressive exogenous models. Additional references to non-linear time series analysis: (Kants and Schreiber), and (Abarbanel) [4].

Among other types of nonlinear time series models, there are models for representing variance variations over time (heteroskedasticity). These models represent autoregressive conditional heteroskedasticity (ARCH), and the collection includes a wide range of representations (GARCH, TARCH, EGARCH, FIGARCH, CGARCH, etc.). Here, changes in variability are related or predicted by recent past values of the observed series. This differs from other possible ideas of locally varying variability, where variability can be modeled as being controlled by a separate time-varying process, as in the double-stochastic model [4].

In a recent analysis work without a model, methods based on wavelet transforms (e.g., locally stationary wavelets and wavelet decomposed neural networks) are recognized. Multiscale methods (often referred to as multi-resolution) expand this time series, trying to illustrate the time dependence on several scales. See also Markov switching multifractal (MSMF) methods for modeling the evolution of volatility. Hidden Markov Model (HMM) is a statistical Markov model in which the simulated system is considered a Markov process with unobservable (hidden) states. HMM can be considered as the simplest Bayesian dynamic network. HMMs are widely used in speech recognition to translate the time series of spoken words into text [1].

5. Fast Fourier transform

Time series metrics or features that can be used for time series classification or regression analysis. A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. The DFT is obtained by decomposing a sequence of values into components of different frequencies.[1] This operation is useful in many fields, but computing it directly from the definition is often too slow to be practical. An FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse (mostly zero) factors.

The difference in speed can be enormous, especially for long data sets where N may be in the thousands or millions. In the presence of round-off error, many FFT algorithms are much more accurate than evaluating the DFT definition directly or indirectly. There are many different FFT algorithms based on a wide range of published theories, from simple complex-number arithmetic to group theory and number theory [5].

6. Conclusion

We described the process, identified methods and means of decomposing the process of modeling complex systems. We also described methods of model synthesis as a means of solving local problems of information transformation in the technology of multilevel intellectual monitoring of trading on the exchange.

We are currently researching the process of developing monitoring intelligent systems to forecast the Australian dollar rate. That is why we believe that our research is valuable nowadays and in future it can be really helpful in modern society.

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