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Abstract. In this paper, cognitive modeling methods were investigated. As a result of the study, it was concluded that the fuzzy cognitive map model is most suitable for solving the forecasting problem. Approaches to the construction of subjective models of the situation are investigated, problems solved with the help of fuzzy cognitive maps are investigated.
To support decision-making in poorly structured dynamic situations, the methodology of cognitive modeling is used, based on the construction of a subjective model of the situation, reflecting the subject's knowledge of the laws of its development. The subjective model of the situation is constructed in an expert way and is presented in the form of an oriented sign graph (cognitive map), in which the vertices are the factors of the situation, and the weighted arcs are the cause-and-effect relationships, the weight of which reflects the strength of the influence of the factors of the situation.

Keywords: Deep learning, Neural networks, rule extraction, Convolutional neural network, Machine learning, Artificial intelligence, explanational artificial intelligence.

1 Introduction

Forecasting time series based on historical data plays an important role in solving a large number of tasks such as forecasting the stock market, macroeconomic indicators of the state, forecasting the financial performance of companies, forecasting temperature and energy consumption. There are a great many problems in which forecasting plays a decisive role.

The time series is governed by two main forces - time and events that affect the change over time in the values of the time series. Most of these events are characterized by some uncertainty. Each value of the time series can be associated with a fuzzy variable with a certain membership function. In this regard, the most interesting for this dissertation research are methods based on the theory of fuzzy sets. Lotfi Zadeh in 1965 introduced the concept of a fuzzy set, thanks to which it is possible to describe qualitative fuzzy concepts and knowledge about the surrounding world, and then operate them to obtain new information [1-5]. The use of this concept allows us to formalize linguistic information for the construction of mathematical models [6-10]. The concept of a fuzzy set is based on the judgment that the elements that make up a given fuzzy set, as well as having common properties, can have it and, therefore, belong to this set to varying degrees. In this case, statements of the form “such and such an element belongs to a given set” lose their meaning, since it is also necessary to indicate the degree of belonging to this set and its properties [11-16].

Thanks to fuzzy set theory, using fuzzy relations and rules, it is possible to create an efficient time series forecasting model with a large number of inputs and one output (forecast).

To support decision-making in poorly structured dynamic situations, the methodology of cognitive modeling is used, based on the construction of a subjective model of the situation, reflecting the subject's knowledge of the laws of its development. The subjective model of the situation is constructed in an expert way and is presented in the form of an oriented sign graph (cognitive map), in which the vertices are the factors of the situation, and the weighted arcs are the cause-and-effect relationships, the weight of which reflects the strength of the influence of the factors of the situation. The sign "+" or "-" is assigned to the directed arcs of the graph, i.e. they can be positive or negative. A positive relationship means that an increase in the value of a factor-cause leads to an increase in the value of a factor-effect, and a negative arc means that an increase in the value of a factor-cause leads to a decrease in the value of a factor-effect.

The tasks solved with the help of cognitive maps are to find and evaluate the influences of the factors of the situation, and to obtain forecasts of the development of the situation on the basis of the calculated influences.

Currently, fuzzy cognitive maps proposed by B. Kosko [17] are widely used to calculate the influences and predictions of the development of a situation. In fuzzy cognitive maps, the strength of influence between factors is set using linguistic values selected from an ordered set of possible strengths of influences, and the values of factors, their increments are also set in linguistic form, and are selected from ordered sets of possible values of a factor and its possible increments - scales of factors and increment scales.

2 Cognitive Modelling

To build a cognitive map that reflects the dynamic properties of the observed situation, it is necessary to determine the scale of the values of factors and their increments.

To build a factor scale, a set of linguistic values of a factor is determined and structured. When determining linguistic values, the absolute values of the factor are used, and not its estimates such as "large", "medium", "small". For example, the linguistic value of temperature might be “so hot that you can barely touch your hand” or “so cold that your hand immediately freezes”, not just “Hot” or “Cold”. With such a definition of the linguistic values of the factors of the situation, an objective standard of its meaning is set - a reference point. Setting an objective standard of the factor value facilitates the work of experts in determining the strength of the influence of factors and reduces expert errors.

If the expert finds it difficult to directly determine the linguistic values of a certain factor, then you can choose a set of objects Z * that have a property that coincides with the name of the evaluated factor. Moreover, different objects of this set should have a different intensity of manifestation of this property.

The structuring of linguistic meanings consists in ordering the elements of the obtained set of linguistic meanings and is based on the method of anchor points and the method of dividing a segment in half, proposed by Thorgerson [18].

Applying this method for each factor $f_i \in F$ an ordered set of linguistic values of the factor $Z_i = \{z_{i1}, z_{i2}, \ldots\ldots, z_{in}\}$ can be determined.

To solve the problems of obtaining a forecast of the development of the situation, it is necessary to determine the current value of the factor z_{ic} and changes in the value of the factor over time on the set Z_i, i.e. increment of the factor value. The current value of the factor is defined as an element $z_{ic} \in Z_i$ of the ordered set Z_i. The increment of the factor value is determined for the current value of the factor and is characterized by the direction of the increment - positive, negative increment and the magnitude of the increment.

The set of ordered values Z_i must be represented in the numerical system X_i, i.e. build a scale. In the theory of measurements, the scale is determined by the triple $\langle Z_i, X_i, \varphi_i \rangle$, where Z_i is the original non-numerical system, X_i is a numerical system, φ_i is a mapping that establishes a homomorphism between the original and numerical systems.

The indices of the elements of the ordered set $Z_i=\{z_{i1}, z_{i2}, \ldots\ldots, z_{in}\}$ are a series of natural numbers $1, 2,\ldots, n$, each of which strictly corresponds to an element of the set of linguistic values of the factor. Those z_i matches 1, z_{i2} matches 2, etc. before z_{in} matches n. Let us display the indices of the elements of the set Z_j on the segment of the numerical axis [0,1]. As a result, we obtain the set of points $X_i=\{x_{i1}, x_{i2}, \ldots\ldots, x_{in}\}$, corresponding to the indices of elements of the set Z_i and, therefore, to the elements themselves $\{z_{i1}, z_{i2}, \ldots\ldots, z_{in}\}$.

Point x_{ic} corresponds to the current state on the interval [0,1]. Positive increments are defined as intervals (segments) of the numerical axis: $p_{+i1}= x_{i(c+1)} - x_{ic}$; $p_{+i2}= x_{i(c+2)} - x_{ic}$; ……; $p_{+i(n-c)}= x_{in} - x_{ic}$, and negative increments are the intervals of the numerical axis: $p_{-i1}= x_{ic} - x_{i(c-1)}$; $p_{-i2}= x_{ic} - x_{i(c-2)}$; ……; $p_{-ic}= x_{ic} - x_1$.

Thus, scales can be obtained for all quantitatively or qualitatively measured factors of the observed situation.

3 Fuzzy Cognitive Maps

The concept of fuzzy cognitive maps is still under development. Various methods of modeling and interpretation of a fuzzy cognitive map are proposed. In this dissertation work, two main approaches are considered: based on the max-product rule and based on the t- and s-norm operators.

The difference between these two approaches lies in the rules of signaling within the fuzzy cognitive map. In the case of sum-product, a weighted sum of inputs for each concept is used, similar to a neural network. In the case of a fuzzy cognitive map using triangular norms, the maxmin composition is used (or any other composition of t- and s-norms, here min is a trivial example of a t-norm and max is a trivial example of an s-norm) [19].
Further, a formal definition of a fuzzy cognitive map will be given, and both mentioned approaches to the interpretation of a fuzzy cognitive map will be considered.
In conclusion, we will consider alternative ways of interpreting a fuzzy cognitive map, proposed in a number of works relatively recently.
Let's give a formal definition of a fuzzy cognitive map: A fuzzy cognitive map is a digraph, the vertices in which are the concepts or key factors in the development of the situation, and the arcs are the cause-and-effect relationships between them.
Let $G = \{ E, W \}$, E - a set of concepts, W - a set of connections (adjacency matrix): w: $E \times E \to [-1, 1]$: $e_i, e_j \in E, w(e_i, e_j) \in W$. For example, the primitive cognitive map of the sanitary state, presented in Fig. 1, can be defined by the following concepts: e1 - the population of the city; e2 - migration of the population to the city; e3 is the level of production modernization; e4 is the number of city dumpsites; e5 - sanitary condition; e6 - diseases per thousand people; e7 is the prevalence of bacteria in the environment.

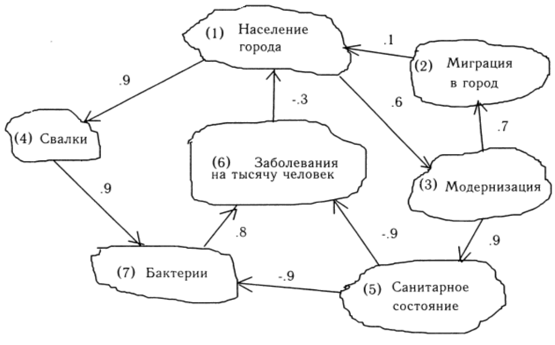

Fig. 1. Fuzzy Cognitive Map "Health Problem"

It is convenient to represent a set of connections in a fuzzy cognitive map in the form of a weighted adjacency matrix, which we will call a cognitive matrix (in accordance with the terminology adopted by Silov [20]). The cognitive matrix for the health issue is summarized in Table 1.

Table 1. Cognitive matrix

	1	***2***	***3***	***4***	***5***	***6***	***7***
1	*0*	*0*	*.6*	*.9*	*0*	*0*	*0*
2	*1*	*0*	*0*	*0*	*0*	*0*	*0*
3	*0*	*.7*	*0*	*0*	*.9*	*0*	*0*
4	*0*	*0*	*0*	*0*	*0*	*0*	*.9*
5	*0*	*0*	*0*	*0*	*0*	*-.9*	*.9*

6	*-.3*	*0*	*0*	*0*	*0*	*0*	*0*
7	*0*	*0*	*0*	*0*	*0*	*.8*	*0*

Each relationship is specified by a value from -1 to 1. Instead of numbers, it is convenient to use linguistic scales. In this case, the expert uses the following steps to determine the connections in the cognitive map:

1. Determines which concepts have a causal relationship.
2. Defines a linguistic scale, consisting of a set of linguistic fuzzy meanings (or terms), for example: "extremely weak", "moderate", "stronger than usual", etc.
3. For each linguistic term, determines the corresponding numerical value in the interval [-1, 1].
4. Specifies the strength of links using linguistic terms.

In the classical case, connections of the form w_{ii} (the main diagonal of the adjacency matrix) are assumed to be zero, but there are approaches that allow extending the functionality of a fuzzy cognitive map to the case of such "loops" [21].

The activity function of the system concepts is defined as *C:* $E_i \rightarrow C_i$. Each node is assigned a measure of activity at time t. It can take values from 0 (no activity) to 1 (active). *C (0)* specifies a vector of initial values of node activity. *C (t)* - vector of states (activity) of nodes at iteration t.

4 Genetic Algorithm for Fuzzy Cognitive Map Learning

Suppose we have a set of 3N lines of historical data (further training material) about the state of concepts in the system. From the point of view of the forecasting problem based on increments of concepts (it was considered in paragraph 2.2.3 "Method of obtaining a forecast"), increments of concepts from the *i-th* iteration to (i + 1) iteration will constitute the initial vector of increments. In this case, the fuzzy cognitive map should show that with a similar initial vector of increments, the values of the concepts will change in such a way that their resulting increments will lead to values at (i + 2) iterations.

Let $A_i(t)$ be the value of the concept $e_i$at time *t*. Based on the specification of the training material given above, we will consider the triplets of rows $A_i(t)$, $A_i(t+1)$, $A_i(t+2)$.

Define $x_i = \frac{A_i(t+1)-A_i(t)}{A_i(t)}$, $y_i = \frac{A_i(t+2)-A_i(t)}{A_i(t)}$. Here x are the initial vectors of increments, *y* – are the resulting vectors of increments.

Let $o_i(t)$be the increment of $e_i$obtained as a result of the forecast on the initial vector x (t).

The learning task is to minimize the error of the fuzzy cognitive map.

Consider the learning process of the FCC in more detail. The weights of a cognitive map are a two-dimensional array, which is decomposed into one-dimensional or, in the language of genetic algorithms, into a chromosome. It should be noted that the initial values of the weights are determined expertly, but unlike the usual painstaking development of the FCC, the expert only needs to indicate any weight value that can show that there is a causal relationship between the two concepts.

Next, non-zero values of the weights are set for new random values, that is, new values for concepts are randomly generated, and the task is to assign them the correct weights, as an expert would do. After that, the initial population is formed (if we draw an analogy with the FCC, then this is the population of weights in the map) and the fitness function is determined, that is, whether this function correlates with the input data (with those causal relationships that were set by the expert). Next, we determine the pool of parents, it is formed randomly and the chromosomes are crossed (the chromosome is the weight in the FCC) that fell into the pool of parents. The crossing boundary is randomly determined. After crossing, we have an array of descendants, from which a new population is formed. Its size is exactly the same as the size of the initial population.

Next, a mutation is made in the offspring population. Upon mutation, a random gene is selected and replaced with a new random value. The cycle of mutation occurs only if the greatest precision is achieved in correlating weights and concepts. The condition for stopping the algorithm is as follows: if the fitness value of the fittest individual is less than the predetermined maximum fitness value, then we go back to the definition of the membership function and form new individuals. If the situation is the opposite, then the algorithm stops and the elite individual is decomposed into an adjacency matrix for the FCC.

5 Forecasting Based on Fuzzy Cognitive Map

The forecast is based on the current initial condition. In the upper part of the work area, the forecast scenario is set. The increments of all concepts of interest are specified here. Concepts, whose values do not change, receive zero increments and a record is displayed for them, for example, Oil price remains constant.

Each concept in the script has a switch. It can be used to disable this concept from forecast modeling. This is similar to removing a concept from the map at the time of the forecast. It should be borne in mind that all transitively closed connections passing through this concept are torn. This option can be useful for experimental forecasts and attempts to assess the role of a particular concept in the forecast.

Figure 2 shows the forecast window of the fuzzy cognitive map "Macroeconomic indicators" for the 3rd quarter of 2009.

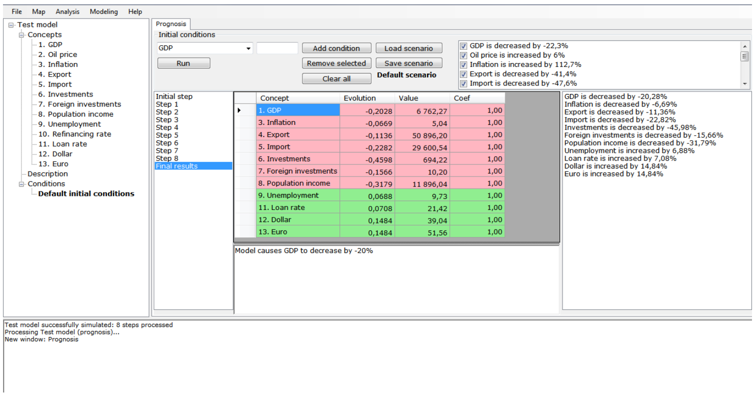

Fig. 2. Results of time series forecasting

The scenario can be saved or loaded using the Save scenario / Load scenario buttons. New conditions are set by the Add condition command. Clear all clears the script.

In the central part of the work area there is a table with the simulation results. It displays the increments of concepts at different steps (steps are switched on the left), as well as the resulting values of the increments. In addition to the increment (indicated in fractions of a unit), the actual predicted value of the concept is indicated. In addition, there is a possibility of "backward adjustment" of concept values (column Coef).

On the right, the modeling table is presented in text form.

In the central lower part there is a window in which judgments about the reasons causing changes in concepts at a particular step are displayed.

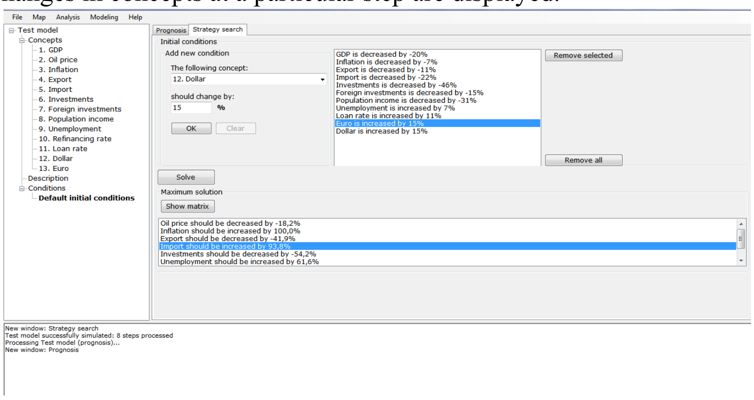

Fig. 3. Strategy searching

The inverse task is launched by the Modeling Strategy search command. Similarly to the forecast window, a set of target conditions is filled. The target condition is the vector of increments of system concepts.

If the solution is not empty, a list of control actions is displayed in text form at the bottom of the workspace, i.e. the increments that need to be made to reach the target increment vector.

The Show matrix button shows the vector of control actions in a tabular form.

In the central part of the work area there is a table of the training sample. Each line corresponds to one set of historical data.

The Roll back any changes button cancels all actions that were performed on the map as a result of training, as well as all changes in the training set. The Save training set button saves the training sample to the model. After that, the model is considered modified.

The Use weight mask option works as follows. If this option is not enabled, then all the weights in the map are filled in during training. If this option is enabled, then the learning algorithm will correct only those weights that are different from zero in the original map, and will make the rest of the weights equal to zero and will not be modified. Thus, it is possible to initially determine between which concepts in the map there is a causal relationship (it is not necessary to determine the sign of this relationship, the map itself will determine during training), and put units (or any other nonzero values) in the corresponding cells of the adjacency matrix. Then start training - only the specified connections will be trained.

This option can be useful if the causal relationships in the map are known. Despite the fact that regardless of this option, training will be performed and the weights in the map are adjusted in such a way as to best match the historical data, the training result can be very far from the expected, for example, the map can create unnecessary and meaningless connections. In addition, with this approach, there is a high probability of the formation of serious dissonances, i.e. situations when a predictive statement always has a low degree of confidence due to almost equal in magnitude negative and positive influences. With predetermined causal relationships that correspond to common sense, the likelihood of the formation of "unnecessary" dissonances is reduced to zero.

Start education team starts training. Depending on the complexity and density of the map, this process can take a long time. The learning process takes place in a separate stream, so you can continue working with the program. The training status - the current generation number, the average fitness value of the generation, and the maximum fitness - are displayed at the bottom of the work area. Training stops when a solution is found with a maximum fitness exceeding 0.99.

Macroeconomics is a good example where it is necessary to closely monitor the interrelationships of all factors influencing the forecast indicator. Here, each indicator is associated with another, and any fundamental changes in one of them entails a chain reaction to the others. In the crisis year of 2009, when there were strong economic shocks, the best way to trace is how much the cognitive map helps to better and more accurately assess the developing situation. Fig. 4 shows forecasts of macroeconomic indicators for the 1st quarter ahead (for the 3rd quarter of 2009).

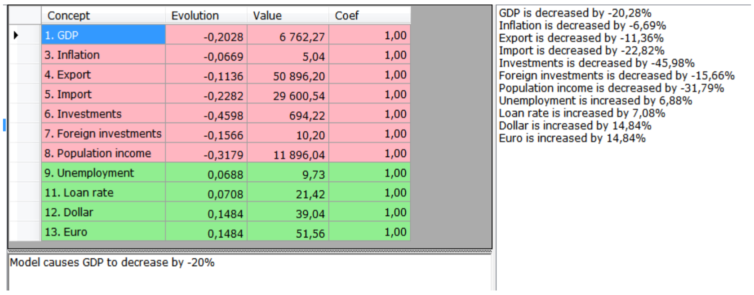

Fig. 4. Forecast of macroeconomic indicators based on fuzzy cognitive map

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7 Conclusion

This paper demonstrated developed environment for modeling a fuzzy cognitive map, which makes it possible to model a fuzzy cognitive map, train it on the basis of a genetic algorithm and obtain high-quality forecasts of the development of the situation.

The testing of the models was carried out on the classic example of forecasting macroeconomic indicators, as well as on the example of forecasting time series with a short relevant part on the example of forecasting socio-economic indicators. As a result of testing, the developed forecasting methods and models show decent forecasting results. And also, it can be seen that thanks to the use of the fuzzy cognitive map module, it becomes possible to process data and receive forecasts of the development of situations even in times of crisis. In other spheres other than macroeconomics, crisis phenomena can manifest themselves in other ways, such as emergency situations in production processes, breaks of contracts for the supply of raw materials. All this can be quickly entered into a fuzzy cognitive map and predicted what this will affect and how the situation will change.

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