Macroeconomic Diagnosis and Prediction Through Software

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Abstract

The competitive and dynamic nature of the business environment in the global economy determines managers to respond to a number of situations for which they need complex information. This has led to the need to develop new tools and to interconnect them with existing systems.

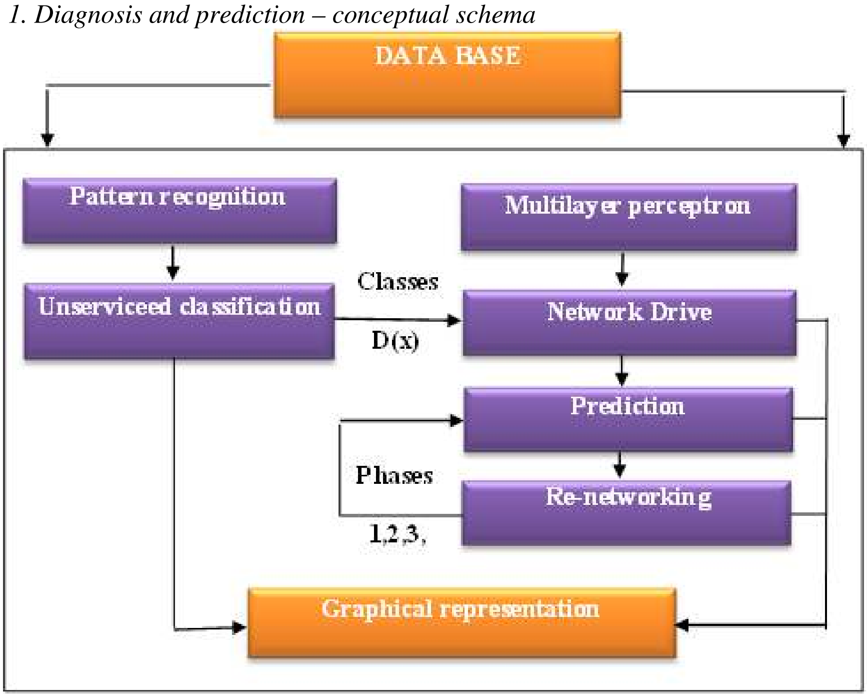
This paper presents aspects of the combined use of artificial intelligence techniques for the evolution of an economic entity based on a set of economic indicators over a long period of time. Based on the set of economic indicators, a measure D (x) can be defined on the space of the forms defined by the set of these indicators, as it will characterize the analyzed economic activity at different times.

Key words: macroeconomic diagnosis, prediction, set of classes, database
J.E.L. classification: M30, M31

1. Introduction

Generally, in the case of forecasting, indicators of an economic nature are used, indicators that are used in different techniques of artificial intelligence. Form Recognition is one of the techniques currently used in predicting and analyzing various economic indicators. To define a form, a set of indicators should be considered at a given time.

Figure no. 1. Diagnosis and prediction – conceptual schema



The plurality of forms is divided into classes through the pattern recognition component of the program, the set of forms is divided into classes. The renumbering of classes that go from negative evolution to positive evolution and whereby economic growth or decline can be highlighted, economic stagnation defines an orderly relation to the multitude of classes that have been achieved through the multiplicity of forms. The conceptual scheme for diagnosis, prediction and graphic representation is presented in Figure 1. (Morariu et al, 2009, pp.213-223), (Iancu, 2016, 102-112).

The database contains as inputs information about the evolution over time of the values of the set of indicators, and the output is represented by a qualitative variable containing the result of the activity evaluation using the classes that were defined by the size D (x).

2. Analyzing the activity of the economic entity using the graphical representation form

In the xOy coordinate system, a graphical representation of the economic activity of an economic entity can be obtained by defining the shapes that are represented in the plane on the Ox axis by points that actually represent the year corresponding to the form and y represents the class to which the respective form belongs . In order to be as plausible as possible, we must have as many classes as possible, given the number of data taken into account. Representing the economic entity's activity from negative evolution to positive evolution is given by class numbering. In this respect, on the set of classes a relation order is defined according to the algorithm described below.

Let be a form x (x_1, x2, ..., x_n) with the characteristics x_i normalized. The importance of the weighting characteristic in conducting these economic analyzes based on economic indicators is given precisely by these weights. These weights can represent some partial-type correlation coefficients that are actually results of a regression model, but at the same time these beams can be determined by some field experts (Morariu et al, 2009, pp.213-223).

In the calculation of the distance D (x) for each space form, the following formula is used (Morariu et al, 2009, pp.213-223):

$$D(x) = \sum_{i=1}^{n} p_i x_i$$

The activity described by form x is measure D (x).

The calculation of the mean of M (c) for each type of class c is calculated using a formula of the type (Morariu et al, 2009, pp.213-223):

$$M(c) = \left(\sum_{x \in c} D(x) \right) / p$$

where x represents those forms belonging to the class c class, and p represents the number of forms in class c. The average of the sizes in the distance D (x) is represented by the mean M (c) formed by the mean of the sizes D (x) belong to a class of type c (Iancu, 2011, pp.49-58).

For example, Class c_1 is in relation "<" to class c_2 if M (c1) <M (c_2). Thus, on the set of classes, a relationship was established on the basis of which the classes would be renumbered to represent the activity analyzed from negative evolution to positive evolution.

We can consider the corresponding Dt_1 (x), Dt_2 (x) sizes for two time intervals t1 and t_2, t_1 <t_2 are considered (Morariu, 2010, pp.87-90), (Morariu et al, 2009, pp.213-223):

- the positive evolution of the activity defined by form x at time t_2 relative to t_1 is given by the relationship of the two sizes where Dt_1 (x) <Dt_2 (x);

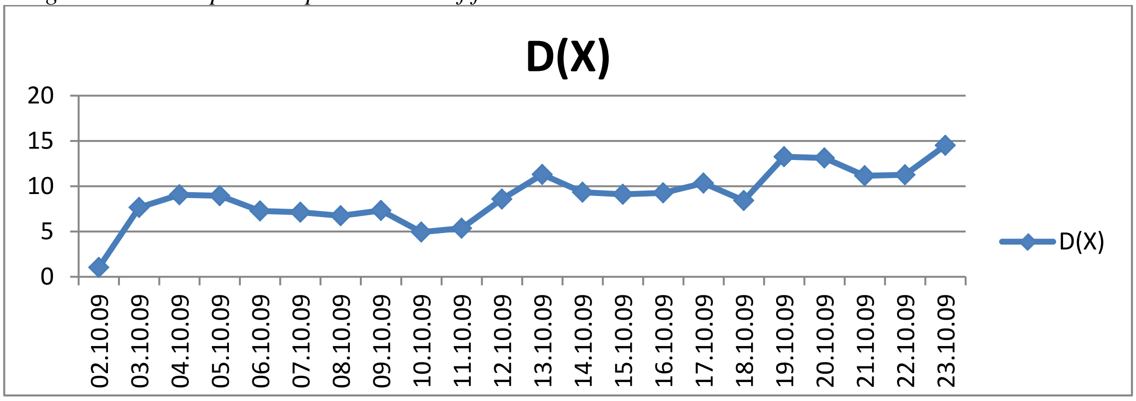
- the stagnation of the activity defined by form x at time t_2 relative to t_1 is given the relationship between the two sizes where Dt_1 (x) = Dt_2 (x);

- the negative evolution of the activity defined by form x at time t_2 relative to t_1 is given by the relation between the two sizes where Dt_1 (x)> Dt_2 (x).

For the mean of M (c) we can make a similar interpretation that will lead to the same result.

The evolution of the activity of an economic entity in the coordinate system xOy can be done with a more accurate graphical representation as follows: a point in the xOy plane is a form in which the Ax represents the time, and on the axis Oy is D (x) corresponding to the x form (figure 2).

Figure no. 2. Graphical representation of forms



3. Experimental results - macroeconomic prediction

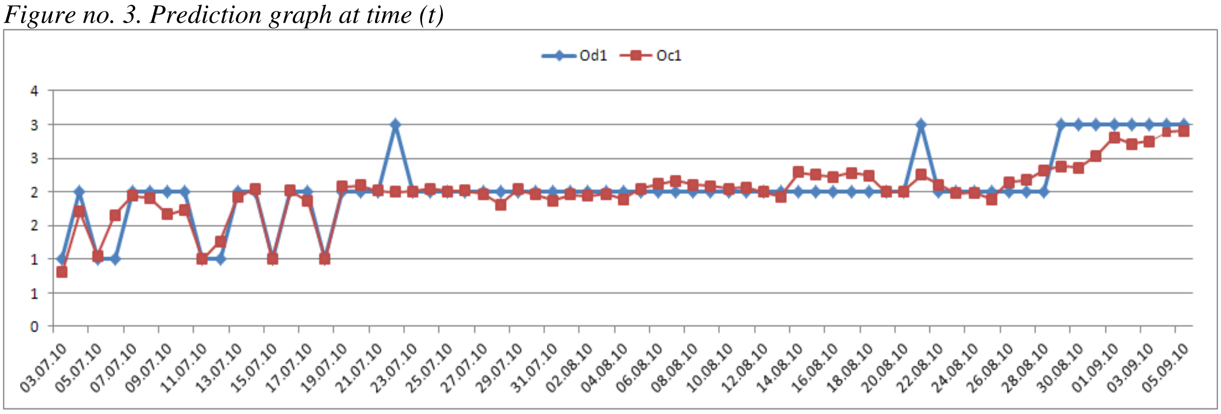
The evolution of the indicators in the table below is considered:

Table no. 1. Indicators used in prediction

Code	Indicators	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
I1	AI	1398	1447	1488	1530	1573	1615	1654	1693	1701	1723	1767	1798
I2	EG	16814	20135	23455	26700	30350	34300	38500	43000	47180	54889	57989	63505
I3	IG	22401	27481	33769	39820	45500	51650	58100	64700	66700	68720	73700	74800
I4	OP	20769	25458	31261	36850	42110	47800	53750	59850	68200	68735	70140	71070
I5	ANE	9473	9290	9295	9305	9320	9335	9350	9365	9545	9845	10430	10980
I6	AE	5791	5669	5775	5875	5960	6025	6095	6145	6212	6401	6504	6709
I7	SMB	1864	2018	2158	2280	2400	2510	2630	2745	2846	2898	2932	2989
I8	AC	1859	1759	1723	1720	1708	1695	1685	1680	1673	1656	1603	1597
I9	FE	2436	2548	2660	2772	2884	2996	3108	3220	3332	3444	3556	3668
I10	FV	4656	5768	6880	7992	9104	10216	11328	12440	13552	14664	15776	16888

The shape features are given by the following macroeconomic indicators: AI, EG, IG, OP, ANE, AE, SMB, AC, FE, FV. The values of these indicators for a given year represent the forms. Considering the fact that the diagnosis cannot be made without diagnosis, it was taken as a time interval for the diagnosis of the years 2004-2009. For prediction, the years ranged between 2010 and 2015.

Figure no. 3. Prediction graph at time (t)



Using the data normalization operation and the unsupervised classification of the data using the threshold algorithm with threshold value = 1 as well as the Euclidean distance result a grouping of the forms in 5 classes numbered according to the given details. Network training rate is a number between 0 and 1 and plays an important role in the convergence of the learning process and the achievement of an optimal solution.

4. Conclusion

Relevant representations can be obtained through classes or D (x). Class representation is even better as the number of classes is higher (the ideal case is when each form belongs to a new class).

For chaotic time series, prediction is a difficult issue to solve. A better approximation can be obtained using specific models for nonlinear systems (Galuskin, 2007), (Graupe, 2007), (Morariu, 2010). Thus, for the solution of complex problems, multilayer neural networks (Nikola, 1998), (Iancu, 2016, pp. 133-135), (Iancu, 2016, pp.25-28) can be used due to the ability to detect nonlinear dependencies in the input data.

The number of k precedent values of type x (t1), x (t2), ..., x (tk) give the predicted value x (tk + 1) of an x variable at a future time tk + 1.

Both the independent variables and the independent prediction independent variable are a function of time, but the predictive variable may be different from the independent variables.

Multivariate prediction can be achieved by using previous values of predictive values of independent values at a given time as well as variable dependent predictions of type x. Univariate predictions can be performed successfully with neural networks.

The neural network training procedure goes with network entrainment for as many years as possible so that the results are as eloquent as possible and then follow the predictions for the next period. The prediction for the next period is achieved by using previously obtained values that are used in the training process.

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