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DIAGNOSIS AND FORECASTING ECONOMY STATE WITH HIDDEN MARKOV MODEL

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ABSTRACT

IThe article is aimed to forecast the future states of economy basing on restricted information about its banking subsystem. The key hypothesis assumes that state of an economic system may be interpreted as a hidden variable. Using several banking indicators as observable variables it is possible to form Hidden Markov models. For known sequence of each observed variable values the appropriate sequence of state classes is determined. The results obtained for all observed variables are aggregated to form the optimal sequence of state classes. The initial models are adjusted due to Baum-Welch algorithm. Then future states of economy as precrisis ones are determined basing on absolute probabilities.

Key words: banking system, state of economy, observed variables, hidden markov model, forecasting.

I. INTRODUCTION

The global financial crisis has affected banking systems of many countries and has performed exactly as banking crisis. However, there is the controversial tendency in fact too. Total system crisis courses financial resources decline both firms and households for. This process stimulates capital flight from banks and landing decrease.

That is why models of rising and spreading crisis have made an interest in scientific world last years. Most of them are devoted to early warning systems and safety criteria for economy [1-2]. Nevertheless assessments of banking system influence on the economy during crisis period are very rare ones.

So the main aim of the paper is to determine the state class of economy basing on banking system variables.

Let's assume that each state may be changed at the beginning of the month and is stable during the month. The number of states is finite. That is why the process of changing states may be defined as stochastic discrete process.

The initial set of states may be divided into separate homogeneous classes $\{S_1, S_2, ..., S_l\}$. Let's assume that the probability of a certain class of state at time t depends on the class of state at time (t–1) only. That is why the process of changing classes may be defined as stochastic discrete Markov process.

State class is not observable directly. That is why the sequence of classes is hidden, unobserved to the researcher. We can only determine the certain value of "state class" indicator indirectly using set of observed and measurable indexes. Here we suggest that banking subsystem indexes have to be used as observable ones. The value of each observed banking index depends on the state class of the economy.

Hence, such situation may be represented by Hidden Markov Model (HMM).

Initially HMM was implemented into technical sphere for solving speech recognition problems [3-4]. However, the modal has become applicable for diagnosis and forecasting some economic processes. The most part of such applications is dedicated to stock markets researches [5]. However, there are lots of examples of HMM successful employment in other spheres. For instance, R. S. Mamon and R. J. Elliott suggest using HMM when studying volatility in growth rate of real GDP and inflation [5]. Authors [6] use hidden markov models in customer relationships dynamics research. Some demography problems are studied in [7]. Human mobility modelling is the object of study in [8]. From the other hand, HMM is not widely used as forecasting tool for the complex economic systems behaviour.

II. RESEARCH SET UP

Each HMM consists of two types of variables:

- hidden variable, which is not directly observable (let it be class of the state of the economy);
- variable, which is observable and measurable (let it be one of banking subsystem indexes).

The following notation may be used to describe HMM [3-4]:

$$\lambda = (P, B, w),$$

$P = \{p_{ij}\}_{L\times L}$, $i,j = [1, L]$ - class of the state transition probability distribution,

L- number of classes;

$B = \{b_j(k)\}$, $j = [1, L]$, $k = [1, M]$, - observed variable probability distribution,

$b_j(k)$ - probability of k-th value of observed variable for class j,

M - number of unique values of observed variable,

$w = (w_1, w_2, ..., w_L)$ - initial class of the state probability distribution.

To form transition matrix P firstly we need to estimate frequency matrix

$$G = (g_{ij})_{L\times L}, \quad (1)$$

$$g_{ij} = \sum_{t=2}^{T} h_t(i, j), \quad (2)$$

g_{ij} -transition frequency from the i-th class to the j-th class, $i, j = [1, L]$,

$$h_t(i,j) = \begin{cases} 1, & X_{t-1} = S_i \wedge X_t = S_j, \\ 0, & \text{othewise.} \end{cases} \quad (3)$$

Finally, transition probabilities must be estimated as follows:

$$p_{ij} = \frac{g_{ij}}{\sum_{j=1}^{L} g_{ij}}. \quad (4)$$

The matrix B is estimated according to the formulas below:

$$b_j(k) = \frac{\sum_{q=1}^{S} d_q(V_k)}{s}, \quad k = \overline{1, M}, \quad (5)$$

s – number of states in the i-th class,

V_k - the k-th unique value for the observed variable,

$$d_q(V_k) = \begin{cases} 1, & X_q^i = V_k, \\ 0, & otherwise. \end{cases} \quad (6)$$

To explore HMM effectively three following problems can be solved:

- for certain sequence of observed variable values determine the probability that the sequence is generated by the HMM;
- for certain sequence of observed variable values determine the appropriate optimal sequence of state classes;
- for certain sequence of observed variable values adjust the HMM to maximize the probability that the sequence is generated by the HMM.

This work is dedicated to the last two problems.

The second problem is solved by Viterbi algorithm, which is represented below [3-5].

Step 1.Determine additional variables.

$$\delta_t(i) = \max_{q_1 q_2 \ldots q_{t-1}} P(q_1, q_2, \ldots, q_t = S_i, O_1, O_2, ..., O_t \mid \lambda), \quad (7)$$

$\delta_t(i)$ - maximum probability that for the given first t values of the observed variable the sequence of classes is finished in the i-th class at the time t.

Step 2. Initialization

$$\delta_1(i) = w_i b_i(O_1), \quad i = [1, L] \quad (8)$$

$$\psi_1(i) = 0 \quad (9)$$

Step 3. Recursion

$$\delta_t(j) = \max_{1\le i\le L}[\delta_{t-1}(i) p_{ij}] b_j(O_t), \quad (10)$$

$$\psi_t(j) = \arg\max_{1\le i\le L}[\delta_{t-1}(i) p_{ij}], \quad t = [2, T], \quad j = [1, L] \quad (11)$$

Step 4.Termination

$$P = \max_{1\le i\le L}[\delta_T(i)], \quad (12)$$

$$q_T = \arg\max_{1\le i\le L}[\delta_T(i)]. \quad (13)$$

Step 5.State sequence backtracking

$$q_t = \psi_{t+1}(q_{t+1}),\ t = T-1, T-2, \ldots, 1 \quad (14)$$

The third problem is solved with Baum-Welch algorithm [3-4]:

Step 1. Determine additional variables.

$\xi_t(i,j) = P(q_t = S_i, q_{t+1} = S_j \mid O, \lambda)$ - the probability of a path being in class S_i at time t and making a transition to class S_{i+1} at time t + 1, given the observation sequence O and the model λ.

$\varphi_t(i) = P(q_t = S_i \mid O, \lambda)$ - the probability of being in class S_i at time t, given the observation sequence O and the model λ.

Then $\varphi_t(i) = \sum_{j=1}^{L} \xi_t(i,j)$.

Step 2. Parameters reestimation.

$$\overline{w}_i = \varphi_1(i);$$

$$\overline{p}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \varphi_t(i)},$$

$$\overline{b}_j(k) = \frac{\sum_{\substack{t=1 \\ O_t = v_k}}^{T} \varphi_t(j)}{\sum_{t=1}^{T} \varphi_t(j)}$$

IV. CALCULATION

We studied the dynamics of Ukrainian economy in 2006-first half 2015(monthly data) [9].

Each state of economy is described as a point in the multidimensional space

$$X_t = (x_{t1}, x_{t2}, \ldots, x_p),$$

p – number of indicators, that describe a state.

To form the classes of states we used such indicators as:

- industrial production index,
- volume of agriculture product,
- volume of construction output,
- customer price index,
- industrial producer price index,
- monthly average wages and salaries,
- registered unemployment,
- load of registered unemployed per 1 vacant work place.

As the banking subsystem indicators we used:

- loans granted by depository corporations (except National Bank of Ukraine)
- loans of households,
- consumer loans,
- loans for house purchase.

To form HMM we need to solve the following problem: how to take into account all possible values of the observed variable and to guarantee:

- the completeness of the observations set
- not very large value of variable .

We suggest to use growth rates of observed variables and to convert initial discrete time series into interval ones. So, let's interpret as the number of intervals of observed variable.

According to the cluster analysis algorithms three homogenous groups of economy states were formed. The first group consists of states which represent 2006-2007 years, February 2008, 2011-2012 years, January-February 2013; the second group contains 2009 year and 2015(first half), the remained states form the third group. Our suggestion is to interpret the first group as comparatively stable class, the second - as crisis class, the third - as precrisis class.

Transition matrix P for three classes is represented below (see formulas (1) - (4)).

Table 1

Transition matrix

Classes	Comparatively stable	Precrisis	Crisis
Comparatively stable	0,94	0,06	0,00
Precrisis	0,04	0,91	0,04
Crisis	0,00	0,06	0,94

Matrix B was calculated for each observed variable according to formulas (5)-(6). Matrixes are represented below (tables 2-5).

Table 2

Matrix B_1 for loans granted by depository corporations

Classes	Intervals			
	V^{B1}_1	V^{B1}_2	V^{B1}_3	V^{B1}_4
	<0,84	[0,84;0,92)	[0,92;1,00)	1,00=<
comparatively stable	0,00	0,00	0,54	0,46
precrisis	0,07	0,13	0,58	0,22
crisis	0,06	0,11	0,72	0,11

Table 3

Matrix B_2 for loans of households

Classes	Intervals			
	V^{B2}_1	V^{B2}_2	V^{B2}_3	V^{B2}_4
	<0,92	[0,92;0,98)	[0,98;1,05)	1,05<
comparatively stable	0,00	0,00	0,56	0,44
precrisis	0,11	0,13	0,69	0,07
crisis	0,06	0,28	0,67	0,00

Table 4

Matrix B_3 for consumer loans

Classes	Intervals			
	V^{B3}_1	V^{B3}_2	V^{B3}_3	V^{B3}_4
	<0,85	[0,85;0,93)	[0,93;1,01)	1,01<
comparatively stable	0,00	0,00	0,50	0,50
precrisis	0,02	0,11	0,60	0,27
crisis	0,06	0,06	0,83	0,06

Table 5

Matrix B_4 for loans for house purchase

Classes	Intervals			
	V^{B4}_1	V^{B4}_2	V^{B4}_3	V^{B4}_4
	<0,92	[0,92;1,00)	[1,00;1,08)	1,08<
comparatively stable	0,00	0,46	0,32	0,22
precrisis	0,04	0,69	0,24	0,02
crisis	0,11	0,56	0,28	0,06

Thus, we have obtained four HMM, which have the common matrix P and vector w, but different matrixes B.

Viterbi algorithm was applied to each HMM to determine the optimal sequence of economy classes for period jan-jun 2015.

Observed variables values for period Jul-Dec 2015 are shown below.

Table 5

Growth rates of observed variables

Period	loans granted by depository corporations	loans of households	consumer loans	loans for house purchase
July 2015	0,98	0,98	0,97	0,99
August 2015	1,00	0,99	1,00	0,98
September 2015	0,95	0,86	0,82	0,93
October 2015	1,03	1,02	1,01	1,04
November 2015	0,96	0,96	0,95	0,99
December 2015	0,94	0,95	0,95	0,96

According to the information about discrete intervals (Table 2 – Table 5) the appropriate sequences of observed intervals were determined. These sequences are used as inputs for Viterbi algorithm (Table 6).

Table 6

Sequences of observed intervals

Period	loans granted by depository corporations	loans of households	consumer loans	loans for house purchase
July 2015	V^{B1}_3	V^{B2}_3	V^{B3}_3	V^{B4}_2
August 2015	V^{B1}_4	V^{B2}_3	V^{B3}_3	V^{B4}_2
September 2015	V^{B1}_3	V^{B2}_1	V^{B3}_1	V^{B4}_2
October 2015	V^{B1}_4	V^{B2}_3	V^{B3}_4	V^{B4}_3
November 2015	V^{B1}_3	V^{B2}_2	V^{B3}_3	V^{B4}_2
December 2015	V^{B1}_3	V^{B2}_2	V^{B3}_3	V^{B4}_2

All models have determined the crisis class of economy during the second half of the 2015 year.

To verify these results k-means procedure was used to form homogenous sets of states for the period 2006-2015. The results correspond with those obtained by Viterby algorithm.

Baum-Welch algorithm was applied to adjust initial four hidden markov models. As the result four new transition matrixes were obtained: $\overline{P}_1$, $\overline{P}_2$, $\overline{P}_3$ and $\overline{P}_4$.

These matrixes were used to estimate four variants of absolute probabilities of each class (comparatively stable, precrisis, crisis) at the first six months of the current 2016 year:

$$g^{kj} = w(\overline{P}_k)^j,$$

g^{kj} - vector of absolute probabilities for the j-th month for the k-th model,

$k \in [1;\ 4]$ - index of the particular hidden markov model,

$j \in [1;\ 6]$ - month's index,

w - initial vector of absolute probabilities.

To calculate the final average absolute probabilities for the j-th month the following formula was used:

$$\overline{g}_i^j = \frac{1}{4}\sum_{k=1}^{4} g_j^{kj},$$

$\overline{g}_i^j$ -average absolute probability of the i-th class for the j-th month,

g_i^{kj} - absolute probability of the i-th class for the j-th month according to the k-th model.

Finally, the following absolute probabilities were obtained for the first six months of the 2016 year:

$$\overline{g} = (0; 0,25; 0,75).$$

VI. CONCLUSION

Obtained results allow to sum up that Hidden Markov Models may be used to identify the future class of states of economic system based on current banking system variables. The advantage of this approach is the possibility to estimate the state of economy using restricted initial information. The accuracy of the assessment increases thanks for using several models based on different observed variables. Four models that were formed by loans granted by depository corporations, loans of households, consumer loans and loans for house purchase have demonstrated corresponding results.

According to the models the Ukrainian economy deepened into crisis at the first half of 2016. Future research should be concerned to including crisis indicators from other economy subsystems as predictors to the model.

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