

# Business Cycle Forecasting Model using Fuzzy Interactive Naive Bayesian Network

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## Abstract

This study presents a business cycle forecasting model using economic indicators based on Fuzzy Interactive Naive Bayesian (FINB) network. FINB classifier is a modified model to enhance the classification capacity by weakening the conditional independence of naive Bayesian network. In particular, it facilitates the construction of an interaction network map consisting of leading indexes, thereby clarifying the degree of influence of a certain index to and from other indexes. The experimental results of the final interaction network map provide valuable information hidden in the prediction mechanism. Particularly, under the changing economic environment in the wake of the global financial crisis of 2008, future economic situations are hard to predict owing to the complexity of financial systems in which increased variables and the heightened interdependencies between them are interwoven within the system. These factors in turn aggravated the fragility of the financial system as a whole, resulting in increased uncertainty in predicting the outlook of the world economy. The proposed interaction network map described here will provide new insight into how the financial mechanism operates, new information pinpointing the main factors of the business cycle.

**Keywords:** Business Cycle, Fuzzy Neural Network, Leading Composite Index, Naive Bayesian Network

## 1. Introduction

New approaches for predicting the cyclical fluctuations of the economy using artificial intelligence have been recently developed. These new approaches include neural networks, wavelet based analysis, support vector machines, and the Bayesian network<sup>2-8</sup>. Under the changing circumstances surrounding the economic situations, we are now experiencing the chaotic characteristics arising from increased complexity and interconnections between global financial networks. The financial markets are exhibiting heightened risks and fragility. Particularly after the financial crisis, there has been growing tendency among economists to apply network technique to financial phenomena to prevent the future systematic collapse<sup>6</sup>.

We propose a forecasting model of the cyclical economic fluctuations based on Fuzzy Interactive Naive Bayesian (FINB) network<sup>1</sup>. The Leading Composite

Indexes (LCI) among economic indicators are used to predict the cyclical economic fluctuations. The widely used Bayesian forecasting method is based on the probability theory of reasoning regarding uncertainties<sup>9,10</sup>. We calculate the weights of the nodes consisting of the leading composite indexes and then construct a map which shows interactions or interdependencies between nodes. The weights represent the strength of influences between nodes in the forecasting mechanism. They are measured and assigned by a neural network called neural Network with Weighted Fuzzy Membership functions (NEWFM)<sup>13-15</sup>. The performance of the proposed model shows a significant level of accuracy while providing a hidden information in the forecasting process.

In this paper, section 2 describes the dataset used to predict the business cycle. The methods of reducing dimensionality and forecasting the business cycle are introduced. In addition, we added the explanations concerning the structure of the proposed model. Section

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three presented the test results obtained, followed by section four, discussion.

## 2. Materials and Methods

### 2.1 Materials

We used economic indexes including leading indexes, coincident indexes, lagging indexes and Gross Domestic Products (GDP) to forecast the business cycle. All of those indexes are closely reflect the economic situations. These composite economic indexes are the key elements in an economic analysis designed to signal the turning point of peaks and troughs, example the booms and recesses, in the business cycle. In particular, leading indexes are compiled using very sensitive and pro-cyclical indicators selected from the overall economic sectors that usually change before the economy as a whole. They are therefore useful as predictors of an economic outlook.

In this paper, 192 components of the leading indexes from Jan 1991 to Dec 2006 are used including inventory circulation indicator, liquidity aggregates of financial institutions, and received machinery orders. These datasets are available from monthly bulletin of the National Statistical Office of Korea. We chose the average of increase in GDP from 1970 as the target class shown in Table 1<sup>8</sup>.

**Table 1.** Data used

Data	Predictor (Number)	Detail	Number of data
Training	LCI (10)	Liquidity aggregates, stock price, inventory circulation, interest rate spread etc.	180
Test	LCI (7)	Liquidity aggregates, construction orders, inventory circulation, consumer expectation etc.	12
Class 1: Peak (less than 5.5% GDP average growth rate) Class 2: Trough (higher than 5.5% GDP average growth rate)			

### 2.2 Business Cycle Forecasting Methodology

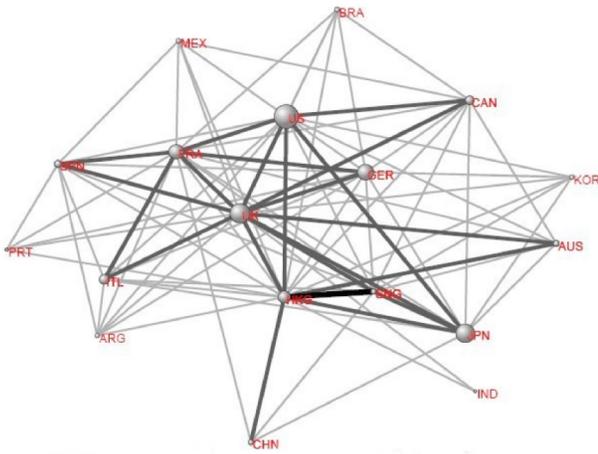
Studies on the business cycle had been an important part of classical economic theory, but it fell out of the economics mainstream after the so-called Keynesian revolution proved that a depression can be overcome by expanding the effective demand and that all the obstacles to full employment can be removed. Thereafter, we forgot a business cycle even exists within capitalism itself. However, Studies on the business cycle began gaining interest particularly after the global financial crisis in 2008.

The global financial crisis was not predicted by mainstream economists and even now its ongoing effects remain unpredictable owing to the complexity of financial systems. Nodes have grown in size and the interconnections between them have multiplied as shown in Figure 1<sup>6</sup>. Thus they have increased the variables and the interwoven complexity of global financial networks, which in turn aggravated the fragility across the financial system as a whole, heightening the uncertainty in the world economy. Under the changing environment of the global financial system, growing interest in network theory has occurred among economists hoping to obtain wisdom from such complex adaptive systems as a tropical rainforest where the chances of a systematic collapse owing to the interdependency among species have been happened. We need new knowledge regarding the degree of distribution of complex financial networks and their interdependencies, which act as a shock-absorber or shock-amplifier within the system. This in turn provides new information able to pinpoint the main factors that propagate such shocks over the whole financial system.

Studies on the business cycle have been conducted mainly using a traditional econometrics approach. The State-Space Markov Switching Model, Neftci Model and Dynamic Stochastic General Equilibrium Mode (DSGE) are the main microeconomic or macroeconomic based models<sup>2,7</sup>. However, many new approaches using information technology such as neural networks and the Bayesian networks have been developed in a wide range of economic fields including business forecasting.

### 2.3 Feature Selection

Feature selection is a very important factor in neural networks for improving the classification accuracy and



**Figure 1.** The global financial networks.

simplifying the forecasting processes by reducing the number of dimensions. Therefore, the best subset, or a compact model, predicting future responses with a smaller variance than a full model is desirable. We applied NEWFM and its feature selection method for reducing the dimensionality that select important inputs while deleting less important inputs<sup>13-15</sup>.

After iterated classification experiment by reducing the number of features one by one, seven of the reduced features among ten of leading indexes resulted in the best average hit rate which is compatible with the maximum level as shown in Figure 2. The number of these

final features reduced using NADM was also identified as the optimum number by using a forward eliminating method of stepwise regression which starts with all candidate variables, and eliminates them one by one; the deletion of such variables improves the model the most, and the process is repeated until no further improvements are possible. As a result, a useful subset of predictors is identified<sup>16</sup>.

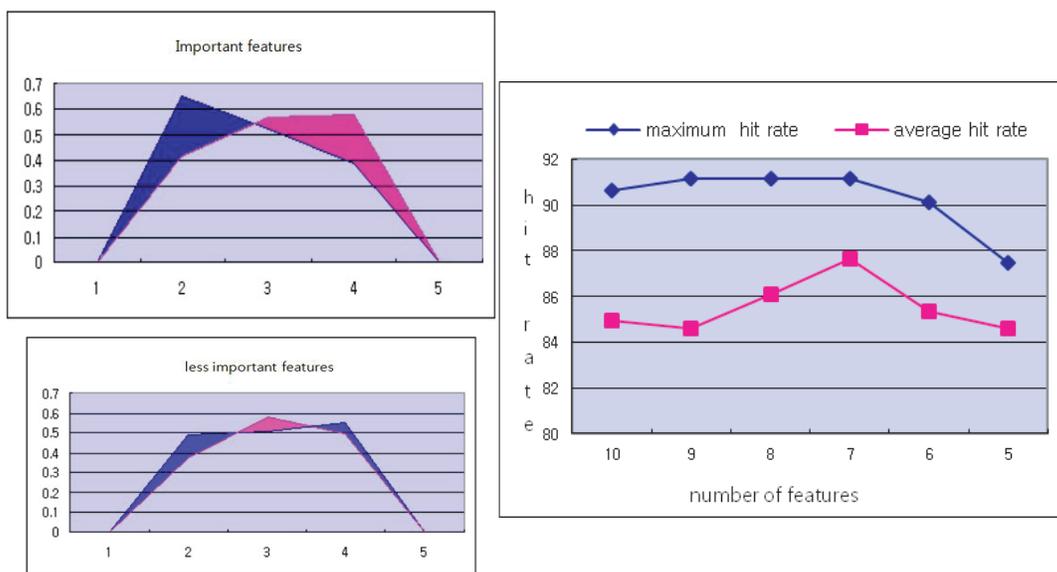
### 2.4 Selection of the Interactive Parent and Calculation of the Weight

We find the relationship among the components of the leading indexes, and then construct an interaction network map consisting of the class and attributes nodes representing the leading indexes.

A target  $A_i$ , denoted by class  $(n_{i,j})$  is defined

$$class(n_{i,j}) = \begin{cases} 1, & n_{i,j} < mean(A_i) \\ 2, & n_{i,j} \geq mean(A_i) \end{cases}$$

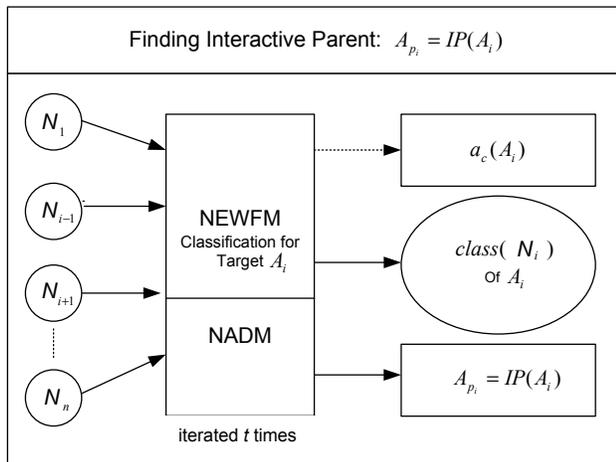
Every index is chosen to be a target index and classified by the other input indexes by NEWFM obtaining classification accuracy of  $A_i$ ,  $A_c(A_i)$ . After  $t$  times iterative experiment of the training and tests, the target index  $A_i$  that has the highest score of hit rate, example  $h(A_{pi})$  is chosen as a parent node for each input node  $A_i$ . We use this  $h(A_{pi})$  with classification accuracy rate for calculating the weight between parent and child nodes Figure 3.



**Figure 2.** Feature selection by NADM.

**Table 2.** Feature selection by stepwise regression

Step	1	2	3	4	5	6	7
Constant	0.9115	0.5645	0.5465	0.5215	0.3908	0.3877	0.3133
A5	1.19	1.11	0.87	0.95	0.83	0.77	0.72
T-Value	8.40	9.18	6.40	6.71	5.62	5.12	4.71
P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A8		0.732	0.748	0.606	0.445	0.365	0.25
T-Value		8.63	9.04	5.43	3.43	2.69	1.63
P-Value		0.000	0.000	0.000	0.001	0.008	0.106
A2			0.50	0.45	0.28	0.29	0.31
T-Value			3.35	2.97	1.66	1.77	1.86
P-Value			0.001	0.003	0.098	0.079	0.064
A3				-0.00013	-0.00020	-0.00021	-0.00027
T-Value				-1.88	-2.70	-2.82	-3.24
P-Value				0.062	0.008	0.005	0.001
A4					0.50	0.60	0.58
T-Value					2.37	2.77	2.71
P-Value					0.019	0.006	0.007
A7						-0.00021	-0.00023
T-Value						-1.85	-1.98
P-Value						0.067	0.049
A6							0.30
T-Value							1.59
P-Value							0.113
S	0.425	0.361	0.352	0.349	0.345	0.343	0.342
R-Sq	27.06	47.68	50.63	51.54	52.96	53.81	54.44



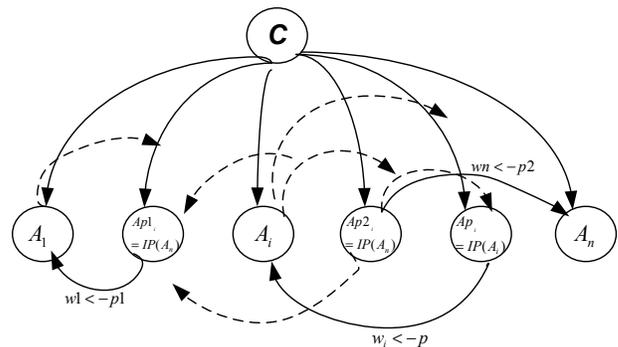
**Figure 3.** Detecting parent nodes.

The weight, example the degree or strength of influence from parent node  $A_{p_i}$  to child node  $A_i$ , as denoted by  $w_{i \leftarrow p}$  is shown in equation (1), where  $t$  is the number of

classification iterations for  $A_i$ ,  $a_c(A_i)$  is the classification accuracy of  $A_i$ , and  $n$  is the number of  $A_s$ .

$$W_{i,p} = \frac{h(A_p)}{t} * a_c(A_i) \text{ for } C = 1, 2, i = 1, 2, \dots, n, \text{ where } i \neq p \quad (1)$$

Here,  $w_{i \leftarrow p}$  represents the degree of interactive relationship from  $A_{p_i}$  to  $A_i$ . The process of constructing a interaction map is shown in Figure 4.



**Figure 4.** Interactive Bayesian network.

### 2.5 Classification of FINB

The naive Bayes model uses the Bayes theorem based on a conditional independence hypothesis. Thus, the naive Bayes classifier is based on two conditions for the features of independent variables and the response variable to be predicted. Based on the NB network, the joint distribution represented by an FINB network is defined as:

$$P(D_1, \dots, D_n, C) = P(C) \prod_{i=1}^n P(D_i | D_p, C) \tag{2}$$

Where C is the class node.

The classification corresponding to an FINB network on samples set S<sub>j</sub> {n<sub>1</sub>, j, ..., n<sub>n</sub>, j}, C<sup>j</sup>, is defined as

$$c_j^* = \arg \max_{c_j \in c} P(C) \prod_{i=1}^n P(n_{ij} | n_{pj}, C) \tag{3}$$

Where

$$P(n_{ij} | n_{p,j}, C) = P(n_{ij} | C) + (P(n_{p,j} | C) - P(n_{ij} | C)) *_{i-p} \tag{4}$$

The expression values are continuous, P(n<sub>ij</sub> | C) and P(n<sub>p,j</sub> | C) in equation (4) are obtained through Gaussian distribution. In this map, the attribute relationships are represented based on interactive parents of the attributes. The method for defining an interactive parents determines the capability of representing the attribute dependencies.

Instead of a Gaussian distribution, we proposed the use of fuzzy distribution in the FINB classifier for the next part of this research. The NEWFM determine the fuzzy distribution, and can obtain the Bounded Sum of the Weighted Fuzzy Membership (BSWFM) after training the data<sup>13-15</sup>. We applied the BSWFM to the FINB classifier and constructed FINB. Figure 5 shows a fuzzy distribution example for a leading index, where the dotted and solid lines show the fuzzy distribution of class 2 for boom and class 1 for recess, respectively<sup>1</sup>.

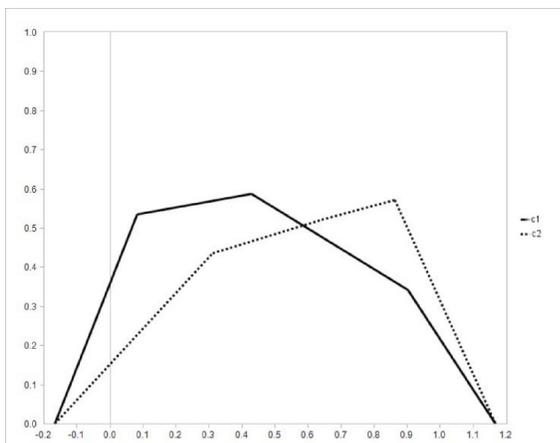


Figure 5. Fuzzy distribution example.

## 3. Results

### 3.1 Test Result of Interaction Network Map

Table 3 shows the weight calculation between the interactive parent node (A<sub>p</sub>) and its target node (A<sub>i</sub>). Figure 6 shows that the two indexes, concerning inventory and liquidity played the most important role influencing one another in the cyclical fluctuations of the economy. Particularly the index related with inventory circulation which is extremely pro-cyclical has a tendency to lead cycle with the stronger impact on both indexes related with imports of machinery and capital goods. We also found that the indexes related with the liquidity of the banking sector exchanged the active interactions with the indexes concerning construction Figure 6. These two indexes are the main factors amplifying and propagating shocks to a real economy by manipulating the available volume of funds and by contracting or activating job creation or the overall production sectors including housing starts. Therefore, for the first time, we can obtain valuable information hidden in the forecasting process.

Table 3. Weight calculation

A <sub>i</sub>	ac(A <sub>i</sub> )	A <sub>p</sub>	h(A <sub>p</sub> )	W <sub>i→p</sub>
A <sub>1</sub>	80.72%	A <sub>2</sub>	1194	0.1927
A <sub>2</sub>	85.93%	A <sub>5</sub>	1436	0.2467
A <sub>3</sub>	81.25%	A <sub>8</sub>	1028	0.1670
A <sub>4</sub>	78.13%	A <sub>2</sub>	1873	0.2926
A <sub>5</sub>	83.33%	A <sub>2</sub>	1514	0.2523
A <sub>6</sub>	73.44%	A <sub>8</sub>	1781	0.2615
A <sub>8</sub>	82.77%	A <sub>6</sub>	1397	0.2312

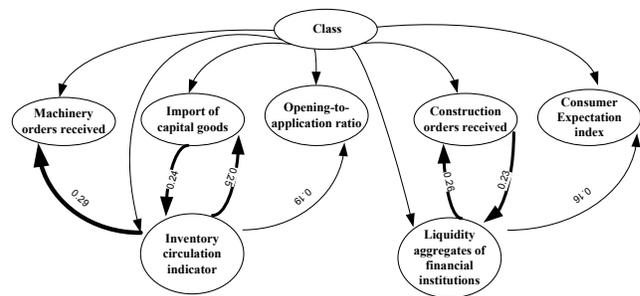


Figure 6. The interaction network map.

### 3.2 Test Results of the Classification Rate

Table 4 shows the classification results representing the cyclical fluctuations of the economy, example peak or

trough of the economic situations. The proposed model represents 83.33% of classification rate, a relatively high level of accuracy considering the nonlinear characteristics of economic data. The performance comparison with other similar Bayesian technique represents the same level of accuracy. However, we can obtain a map which can be easily understood and moreover obtain new valuable information regarding the interwoven dependencies between the nodes (Table 4).

**Table 4.** The comparison of functions

	Classification function(rate)	Other function (reducing dimensionality)	Interaction between nodes
Proposed model	83.33%	available	simple
Bayesian models		unavailable	complicated
TAN	83.33%		
NaiveBayes	83.33%		

## 4. Discussion

This study proposed a new approach to find the relationships between the leading composite indexes in the cyclical economic fluctuations forecasting. Here we used an interactive network map provided by the FINB network. We found that two indexes related with the inventory of goods and the liquidity of the banking sector played the most important role in the forecasting mechanism. Thus we can obtain for the first time new information hidden in the prediction process. In the wake of the global financial crunch, network analyzers began gaining interest in applying their techniques to economic sphere. This proposed interaction map regulating financial networks will provide new insight into the pressing problems facing the changing economic situations, thereby sustaining a stable business cycle, while reducing the chances of a future systematic collapse. The forecasting performance of the proposed model shows relatively good results considering the nonlinear characteristics of economic data. However, further efforts will be needed to enhance the accuracy of the classification rate. The development of the more sensitive and pro-cyclical economic indicators is the most important factor in improving the forecasting capability.

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