A GA-based Input Selection Approach for Neural Networks Modeling :Application to Bankruptcy Prediction

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Abstract

Prediction of corporate failure using past financial data is a well-documented topic. Early studies of bankruptcy prediction used statistical techniques such as multiple discriminant analysis, logit, and probit. Recently, however, numerous studies have demonstrated that artificial intelligence such as neural networks can be an alternative methodology for classification problems to which traditional statistical methods have long been applied.

In building neural network model, the selection of independent and dependent variables should be approached with great care and should be treated as model construction process. Irrespective of the efficiency of a learning procedure in terms of convergence, generalization and stability, the ultimate performance of the estimator will depend on the relevance of the selected input variables and the quality of the data used. Approaches developed in statistical methods such as correlation analysis and stepwise selection method are often very useful. These methods, however, may not be the optimal ones for the development of neural network model.

In this paper, we propose a genetic algorithms approach to find an optimal or near optimal input variables for neural network modeling. The proposed approach is demonstrated by applications to bankruptcy prediction modeling. Our experimental results show that this approach increases overall classification accuracy rate significantly.

1. Introduction

Today, Korean financial institutions are paying a heavy price for their indiscriminate practices. Corporate bankruptcies have put several institutions on the brink of insolvency. Many others will be merged with or acquired by other financial institutions. Surviving institutions are rushing to put in place a corporate credit rating system, but are facing difficulties due to a lack of data accumulation and scientific credit rating methods.

The present research pertains to a corporate failure prediction modeling which can provide a basis for credit rating system. Bankruptcy prediction, through classification of known cases and generalization to other cases, has been a subject of study for almost 35 years. Accurate prediction of bankruptcy is important to investors, creditors and auditors. An accurate prediction model can help shareholders, creditors and governments avoid heavy losses stemming from sudden bankruptcies and could help alert auditors from potential going concern problems. Bankruptcy prediction is a difficult problem because there are potentially many unobservable factors that can determine whether an entity will declare bankruptcy and the timing of such an event. In spite of the potential moderating effects of unobservable strategic factors, there has been an interest in quantitative models for predicting bankruptcy based on observable, predominantly financial, data pertaining to an entity (Boritz *et al.*, 1995).

Most of the bankruptcy prediction studies have traditionally used statistical techniques since the study of Beaver in 1966. Recently, however, numerous studies have demonstrated that artificial intelligence such as neural networks can be an alternative methodology for classification problems to which traditional statistical methods have long been applied. In building neural network model, the selection of independent and dependent variables should be approached with great care and should be treated as model construction process. Irrespective of the efficiency of a learning procedure in terms of convergence, generalization and stability, the ultimate performance of the estimator will depend on the relevance of the selected input variables and the quality of the data used. Approaches developed in statistical methods such as correlation analysis and stepwise selection method are often very useful. These methods, however, may not be the optimal ones for the development of neural network model.

This study proposes a genetic algorithms (GAs) approach selecting optimal or near optimal input variables for corporate failure prediction modeling. The remainder of this paper is organized as follows. The following section provides a brief description of prior research on bankruptcy prediction modeling. Section 3 describes the search process of GAs. Section 4 explains the input selection approach using genetic search approach. Section 5 reports the experiments and empirical results of bankruptcy prediction application. The final section discusses the conclusions and future research issues.

2. Previous Research

Prediction of corporate failure using past financial data is also a well-documented topic. Early studies of bankruptcy prediction used statistical techniques such as multiple discriminant analysis (Altman, 1968, 1983), logit (Ohlson, 1980), and probit (Zmijewski, 1984). Since 1980's, however, numerous studies have demonstrated that artificial intelligence such as neural networks (NNs) can be an alternative methodology for classification problems to which traditional statistical method have long been applied (Back *et al.,* 1997; Bell, 1997; Boritz and Kennedy, 1995; Chung and Tam, 1992; Etheridge and Sriram, 1997; Fletcher and Goss, 1993; Jo *et al.,* 1997; Odom and Sharda, 1990; Salchenberger *et al.,* 1992; Shin and Han, 1998a; Shin *et al.,* 1998; Tam and Kiang, 1992; Wilson and Sharda, 1994). In particular, a number of recent studies have demonstrated that hybrid methodology of artificial intelligence also can be an alternative methodology (Back *et al*., Barbro et al., 1996; Shin and Han, 1998a; Lee and Cha, 1996).

Irrespective of modeling methods, the selection of independent variables should be approached with great care since the variable set used greatly affects prediction accuracies. Most of the researchers frequently have been used financial ratios derived from company's financial statement to build the prediction models. Table 1 illustrates the financial variables that are frequently used in bankruptcy prediction studies.

Table 1. Independent variable list in previous research

Variable set	Variable name	Description
Growth (5)	TAG	Total Asset Growth
	TFAG	Tangible Fixed Asset Growth
	OEG	Owner's Equity Growth
	NSG	Net Sales Growth
	NIG	Net Income Growth
Profitability (13)	OITA	Ordinary Income to Total Asset
	NITA	Net Income to Total Asset
	OIWC	Operating Income to Working Capital
	OPITA	Operating Income to Total Asset
	NIOE	Net Income to Owner's Equity
	OIS	Ordinary Income to Sales
	NIS	Net Income to Sales
	OPIS	Operating Income to Sales
	TSI	Total Sales Income
	FES	Financial Expenses to Sales
	FEOI	Financial Expense to Operating Income
	TIE	Times Interest Earned
	NID	Net Income to Dividend
Leverage (11)	OETA	Owner's Equity to Total Asset
	CACL	Current Asset to Current Liability
	QACL	Quick Asset to Current Liability
	FAOE	Fixed Asset to Owner's Equity
	FAOELTL	Fixed Asset to Owner's Equity and Long Term Liability
	CLFLOE	Current Liability and fixed Liability to Owner's Equity
	FLOE	Fixed Liability to Owner's Equity
	TBBPTA	Total Borrowings and Bonds Payable to Total Asset
	FANWC	Fixed Asset to Net Working Capital
	NWCTA	Net Working Capital to Total Asset
	AETA	Accumulated Earning to Total Asset
Cash Flow (5)	CFTL	Cash Flow to Total Liability
	CFS	Cash Flow to Sales
	CFTBBP	Cash Flow to Total Borrowings and Bonds Payable
	CFTA	Cash Flow to Total Asset
	CFCL	Cash Flow to Current Liability
Activity (5)	TAT	Total Asset Turnover
	NWCT	Net Working Capital Turnover
	FAT	Fixed Asset Turnover
	IT	Inventory Turnover
	RT	Receivable Turnover
Size (2)	S	Sales
	TA	Total Asset
Others (6)	CATA	Current Asset to Total Asset
	NIDTL	Net Income and Depreciation to Total Liability
	QATA	Quick Asset to Total Asset
	CLTA	Current Liability to Total Asset
	STBLTDMS	Short-Term Borrowing and Long-Term Debt to Monthly Sales

Beside financial ratio, other variables such as cash flow data(Aziz and Lawson, 1989; Gentry *et al*., 1985; Gombola and Ketz, 1983), stock market information(Im, 1990; Aharony *et al*., 1980; Clark and Weinstein, 1983; Pettway and

Sinkery, 1980; Queen and Roll, 1987), general price level (Ketz, 1978; Mensah, 1983; Norton and Smith, 1979), capitalization of leases(Elam, 1975), macroeconomic variables(Foster, 1977; Mensah, 1984), distribution of financial ratios(Barniv, 1990; Dambolena and Khoury, 1980), average of debt and note(Foster, 1977; Marais *et al*., 1984), and value added accounting information(Kang, 1991) are also used in some studies.

Table 2 and 3 show the input variable sets that have been used in previous research. In particular, Table 3 illustrates the input variable sets used in Korean bankruptcy studies. As we can see in the table, the input variable sets vary among researchers, although some of the variables are used in common. This is partly due to the fact that the economic situations, the target industries and the size of the firm are different. So the finding optimal input variable for bankruptcy prediction model is rather a contingent task.

Table 2. Variables used in previous research

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
NITA	♦	♦	♦		♦			♦	♦	♦	♦	♦	♦	♦
OIWC				♦			♦				♦			
NIOE						♦								
NIS				♦			♦				♦			
FES											♦			
FEOI									♦					
NID						♦	♦							
CACL	♦		♦				♦	♦	♦	♦	♦	♦	♦	
QACL			♦	♦			♦				♦		♦	
FAOELTL											♦			
CLFLOE									♦					
TBBPTA	♦		♦		♦						♦			
FANWC										♦				
NWCTA	♦	♦	♦										♦	
AETA		♦							♦	♦		♦	♦	♦
CFTL	♦					♦								
CFS			♦				♦							
CFTBBP			♦				♦							
CFTA			♦				♦	♦						
CFCL			♦	♦			♦			♦				
TAT											♦			
NWCT											♦			
S		♦					♦			♦			♦	
TA		♦					♦		♦			♦	♦	
CATA			♦					♦				♦		♦
QATA			♦			♦	♦			♦		♦		♦
FLTA							♦				♦			
CLTA											♦			
STBLTDMS						♦								

(1) Beaver (1966) (2) Altman (1968) (3) Deakin (1972)
(4) Edminster (1972) (5) Pinches *et al.* (1973) (6) Blum (1974)
(7) Elam (1975) (8) Libby (1975) (9) Altman *et al.* (1977)
(10) Ohlson (1980) (11) Dambolena *et al.* (1980) (12) Frydman *et al.* (1985)
(13) Odom *et al.* (1990) (14) Raghupathi *et al.* (1992)

Table 3. Variables used in previous research in Korea

	1	2	3	4	5	6	7	8	9	10	11	12	13
TAG										♦			
TFAG							♦						
OEG										♦			
NSG		♦						♦		♦			
NIG										♦			
OITA	♦				♦			♦		♦	♦		
NITA												♦	
OPITA							♦					♦	
NIOE			♦	♦			♦	♦		♦			
OIS										♦			
NIS									♦	♦			♦
OPIS				♦		♦		♦		♦			
TSI				♦	♦			♦					
FES										♦			

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
TIE						♦		♦				♦	
NID										♦			
OETA									♦	♦		♦	♦
CACL	♦	♦	♦	♦			♦	♦		♦	♦		
QACL								♦		♦		♦	
FAOE				♦			♦	♦		♦			
FAOELTL	♦	♦		♦				♦		♦			
CLFLOE			♦	♦	♦	♦	♦	♦			♦	♦	
FLOE								♦					
NWCTA	♦	♦	♦	♦		♦		♦		♦			
AETA	♦	♦	♦	♦	♦	♦		♦			♦		
CFTL											♦		
CFTA							♦	♦		♦			
CFCL						♦		♦					
TAT	♦	♦	♦		♦	♦		♦	♦			♦	♦
NWCT		♦			♦		♦	♦					
FAT		♦		♦	♦			♦					♦
IT										♦			
RT		♦						♦					
CLTA										♦	♦		♦

(1) Korean bank (1982) (2) Ji, C. (1983) (3) Jeon, C. O. (1984) (4) Park, C. G. (1984)
(5) Jung, J. S. (1985) (6) Huh, Y. B. (1986) (7) Kim, K. W. (1987) (8) Kim, J. K. (1987)
(9) Song, I. M. (1987) (10) Lee and Oh (1990) (11) Hwang, S. H. (1991) (12) Kang, C. S. (1991)
(13) Lee, K. W. (1993)

3. Genetic Algorithm Technique

GAs are stochastic search techniques that can search large and complicated spaces on the ideas from natural genetics and evolutionary principle (Davis,1991; Holland, 1975; Goldberg, 1989). They have been demonstrated to be effective and robust in searching very large spaces in a wide range of applications (Colin, 1994; Han *et al*., 1997; Koza, 1993; Shin and Han, 1998c). GAs are particularly suitable for multi-parameter optimization problems with an objective function subject to numerous hard and soft constraints.

The financial application of GAs is growing with successful applications in trading system (Colin, 1994; Deboeck, 1994), stock selection (Mahfoud and Mani, 1995), portfolio selection (Rutan, 1993), bankruptcy prediction (Kingdom and Feldman, 1995), credit evaluation (Shin and Han, 1998c; Walker *et. al*., 1995) and budget allocation (Packard, 1990).

GAs perform the search process in four stage: initialization, selection, crossover, and mutation (Davis, 1991; Wong & Tan, 1994). Fig 1 shows the basic steps of genetic algorithms.

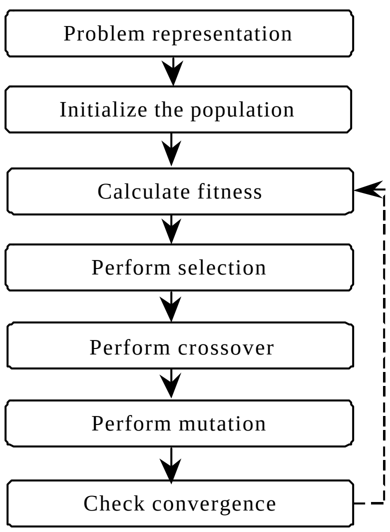

Figure 1. Basic steps of genetic algorithms

In the initialization stage, a population of genetic structures (called chromosomes) that are randomly distributed in the solution space, is selected from the starting point of the search. After the initialization stage, each chromosome is evaluated using a user-defined fitness function. The goal of the fitness function is to numerically encode the performance of the chromosome. For real-world applications of optimization methods such as GAs, the choice of the fitness function is the most critical step.

The mating convention for reproduction is such that only the high scoring members will preserve and propagate their worthy characteristics from generations to generation and thereby help in continuing the search for an optimal solution. The chromosomes with high performance may be chosen for replication several times whereas poor-performing structures may not be chosen at all. Such a selective process causes the best-performing chromosomes in the population to occupy an increasingly larger proportion of the population over time.

Crossover causes to form a new offspring between two randomly selected 'good parents'. Crossover operates by swapping corresponding segments of a string representation of the parents and extends the search for new solution in far-reaching direction. The crossover occurs only with some probability (the crossover rate). There are many different types of crossover that can be performed: the one-point, the two-point, and the uniform type (Syswerda,1989).

Mutation is a GA mechanism where we randomly choose a member of the population and change one randomly chosen bit in its bit string representation. Although the reproduction and crossover produce many new strings, they do not introduce any new information into the population at the bit level. If the mutant member is feasible, it replaces the member which was mutated in the population. The presence of mutation ensures that the probability of reaching any point in the search space is never zero.

4. Input Selection Approach Using GAs

In setting up the genetic optimization problem, we need the parameters that have to be coded for the problem and an objective or fitness function to evaluate the performance of each string. The parameters that are coded are the input variables for neural networks model. The varying parameters generate a number of variable sets.

The GAs maintain a population of strings which are chosen at random. This initialization allows the GAs to explore the range of all possible solutions, and this tends to favor the most likely solutions. The task of defining a fitness function is always application specific. In this study, the objective of the system is to find an optimal or near optimal input variable set which shows the highest hit ratio. We apply the hit ratio of the model to the fitness function for this study. The genetic operators such as crossover and mutation which are described in the previous section are used to search for the optimal solutions. These are done by the software package Predict™ by Neural ware Inc.

5. Experiments and Results

5.1 Data Collection

The data set contains 528 mid-size manufacturing firms (externally audited firms) which filed for bankruptcy (264 cases) and non-bankruptcy (264 cases) during the period 1995-1997. The data was arbitrarily split into a training set, consisting of 424 cases, a test set consisting of 52 cases, and validation set consisting of 52 cases. We select 43 financial variables among more than 100 financial ratios that are frequently used to predict corporate bankruptcy by simple statistic analysis such as independent-samples t-test (between input variable and output variable) and experts' judgment. Table 4 shows the pre-selected variables for this study.

Table 4. Pre-selected variables

Category	Variable	Name	Category	Variable	Name
Size (2)	x1	Sales		x23	Current Asset to Current Liability
	x2	Owner's Equity		x24	Current Liability to Total Asset
Productivity (2)	x3	Ratio of Value Added to Liabilities & Net Worth		x25	Accumulated Earning to Total Asset
	x4	Ratio of Value Added to Net Sales		x26	Stockholder's Equity to Total Asset
Growth (3)	x5	Sales Growth Rate		x27	Total Borrowings to Liability & Stockholder's Equity
	x6	Inventory Growth Rate		x28	Total Borrowing to Sales
	x7	Total Assets Growth Rate	Trend (1)	x29	Growth rate of Financial Expense to Liabilities
Profitability (10)	x8	Interest & Discount Expense to Sales	Activity (5)	x30	Payables Turnover
	x9	Loan Utility Coefficient		x31	Net Working Capital to Sales
	x10	Net Income to Sales		x32	Working Capital to Sales
	x11	Cost of Sales Ratio		x33	Inventory Turnover

	x12	Break-even point Ratio		x34	Total Asset Turnover
	x13	Net Interest & Discount expense to Sales	Cash Flow (9)	x35	Cash Flow after Operating to Total Borrowing
	x14	Times Interest Earned		x36	Cash Flow after Operating to Total Debt
	x15	Net Income to Stockholder's Equity		x37	Cash Flow after Operating to Financial Expense
	x16	Ordinary Income to Liability & Stockholder's Equity		x38	(Sales Income/financial Income) to Financial Expense
	x17	Net Income to Liability & Stockholder's Equity		x39	Cash Flow after Pay Interest to Total Debt
Leverage (11)	x18	1/(Fixed Asset to Owner's Equity and Long Term Liability)		x40	Cash Flow after Pay Interest to Financial Expense
	x19	Short-term Borrowing to Total Borrowing		x41	Cash Flow before investment to Total Borrowing
	x20	Quick Ratio		x42	Cash Flow before investment to Financial Expense
	x21	Receivables to Payables		x43	Cash Flow after investment to Financial Expense
	x22	Net Working Capital Ratio			

5.2 Experiments

In this study, three groups of determining the selecting method of input variables have been proposed. Group A is based on the practical justification. For this group, we have had experts designate the importance of an input variable(financial ratio) by assigning the qualitative values. We have selected some credit analysts from organization such as National Information & Credit Evaluation and Korea Investors Service and from the credit analysis department of a commercial bank. After considering all the experts' opinion, A1 has been organized by the top-ten important variables among the pre-selected ones, and A2 by the most important variable from each category.

Also three methods are proposed by statistical techniques. Set B1 is formed by the t-test of univariate analysis, and Set C1 and C2 are formed by the stepwise selection method of logit and multiple discriminant analysis. Also Set D1, D2, D3, D4 are formed using the two-step approach(the stepwise selection method following the univariate analysis).

Finally using the GAs, Set E1 is organized by the variables that show high level of fitness values. The genetic algorithms is built with the software package Predict^{TM} supported by Neural Ware Inc. Each method for input variable selection is summarized in table 5.

Table 5. Model specification

Group	Method	Set	Description
A	Expert judgment	A1 A2	Top-ten variables by importance Top variable by each category
B	Univariate analysis (t-test)	B1	Top-ten variables in significant
C	Stepwise selection method	C1 C2	Logit_stepwise MDA*_Stepwise
D	Two step approach : apply the stepwise selection method after screening by univariate analysis	D1 D2 D3 D4	Logit_stepwise using variables that show less than 1% of p-value from t-test MDA_stepwise using variables that show less than 1% of p-value from t-test Logit_stepwise using variables that show over absolute value 0.2 of correlation coefficient from correlation analysis MDA_stepwise using variables that show over absolute value 0.2 of correlation coefficient from correlation analysis
E	Genetic Algorithm	E1	High level of fitness values

*Multiple discriminant analysis

Table 6 illustrates selected input variable sets for the experiments. The architecture of Neural network is a three-layer-perceptron with back-propagation algorithms, which consist of input layer, hidden layer, and output layer. The number of hidden node is that of input nodes, and the output value is a continuous value from 0(bankrupt) to 1(nonbankrupt).

Table 6. Selected variables

A1	x1, x2, x8, x10, x11, x13, x26, x27, x30, x33
A2	x1, x4, x5, x8, x27, x29, x33, x36
B1	x2, x13, x16, x17, x20, x22, x24, x25, x26, x27
C1	x1, x3, x5, x7, x11, x13, x22, x24, x25, x29, x31
C2	x1, x3, x5, x6, x7, x11, x13, x24, x25, x29, x31
D1	x3, x6, x11, x13, x17, x22, x24, x25, x29, x31
D2	x1, x3, x6, x11, x13, x17, x24, x25, x29, x31, x32
D3	x1, x3, x13, x20, x24, x26, x29, x31

D4	x1, x3, x13, x24, x26, x31
E1	x3, x8, x13, x24, x25, x26, x29, x31, x35, x36

5.3 Result

Table 7 represents average hit ratio of each experiment set. To mitigate instability due to sampling error, we randomly replicate the selection of data subset five times (set 1, 2, and 3). As shown in Table 7, the prediction accuracy of the input variable set derived from genetic search(E1) outperforms the other sets, followed by Group D Sets using a two step approach. The variable sets assigned by human experts' judgment(A1, A2) shows the least predictive performance. These results demonstrate that the input selection approach based on GAs is a very effective method for modeling the neural network for bankruptcy prediction.

Table 7 Hit ratios of all experimental sets

(cut-off: 0.5)

	Train	Test	Validation
A1	77.88%	76.92%	72.31%
A2	76.56%	74.23%	71.54%
B1	80.80%	80.77%	79.23%
C1	84.72%	82.69%	81.92%
C2	84.20%	83.08%	81.54%
D1	82.55%	81.92%	82.69%
D2	83.96%	85.00%	83.08%
D3	82.59%	83.08%	81.54%
D4	81.89%	81.92%	81.92%
E1	85.85%	85.77%	86.54%

We use the McNemar tests to examine whether the predictive performance of the GAs method is significantly higher than of other input variable selections. The McNemar test is a non parametric test of the hypothesis that two related dichotomous variables have the same means. This test is useful for detecting changes in responses due to experimental intervention in 'before and after' designs using the chi-square distribution. Since we are interested in the correct prediction of cases, the measure for testing is the prediction accuracy rate. Table 8 shows the results of McNemar tests to compare the prediction ability between benchmark models and GAs model.

As shown in Table 8, GAs model has the higher prediction accuracy than any other benchmark models proposed in this study. Results show that the GAs model performs significantly better than expert choice(A1, A2) and Univariate analysis model(B1) at a 1% level, multiple discriminant analysis model(C2) and hybrid selection model(D3, D4) at a 5% level, also better than logit model(C1) at a 10% level. Also, table 8 shows that expert choice model(A1, A2) performs significantly less than GAs model(E1) and other statistical evaluation methods(C1, C2, D1, D2, D3, D4) at a 1% level.

Table 8 McNemar values for the pairwise comparison of performance between models

(Significant)

	A2	B1	C1	C2	D1	D2	D3	D4	E1
A1	0.9062	0.0046***	0.0006***	0.0009***	0.0001***	0.0001***	0.0003***	0.0002***	0.0000***
A2	-	0.0158**	0.0007***	0.0008***	0.0004***	0.0001***	0.0010***	0.0005***	0.0000***
B1	-	-	0.2295	0.3268	0.0636*	0.0525*	0.2632	0.2100	0.0031***
C1	-	-	-	1.0000	0.8145	0.5488	1.0000	1.0000	0.0518*
C2	-	-	-	-	0.6476	0.3438	1.0000	1.0000	0.0367**
D1	-	-	-	-	-	1.0000	0.6291	0.8238	0.1003
D2	-	-	-	-	-	-	0.2891	0.5811	0.1237
D3	-	-	-	-	-	-	-	1.0000	0.0259**
D4	-	-	-	-	-	-	-	-	0.0376**

(*** Significant at 1% , ** Significant at 5%, * Significant at 10%)

6. Concluding Remarks

The selection of independent and dependent variables is critical process in model building processes. Irrespective of the efficiency of a learning procedure in terms of convergence, generalization and stability, the ultimate performance of the estimator will depend on the relevance of the selected input variables and the quality of the data used.

In this paper, we propose a genetic algorithms approach to find the optimal input variables for neural network modeling, and compare the performance with other statistical methods. The results show that input variable selection method using genetic algorithms for bankruptcy prediction modeling is superior.

This paper has several limitations. First, the input data is quite limited. Because of the easiness of data acquisition and the objectivity, we use only financial ratios. It is necessary to extend the qualitative factor to improve the results.

Second, there are several control factors to increase the efficiency of the model in neural network. In this study, after fixing some control factors for finding the optimal input variable selection method, the experiment for prediction is performed. But as a next research step, further improvements may be obtained by varying the control factor such as the number of hidden node and hidden layer, training method, and transfer function.

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