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Instance Selection Using Genetic Algorithms for an Intelligent Ensemble Trading System

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Abstract

Instance selection is a way to remove unnecessary data that can adversely affect the prediction model, thereby selecting representative and relevant data from the original data set that is expected to improve predictive performance. Instance selection plays an important role in improving the scalability of data mining algorithms and has also proven to be successful over a wide range of classification problems. However, instance selection using an evolutionary approach, as proposed in this study, is different from previous methods that have focused on improving accuracy performance in the stock market (i.e., Up or Down forecast). In fact, we propose a new approach to instance selection that uses genetic algorithms (GAs) to define a set of target labels that can identify the buying and selling signals and then select instances according to three performance measures of the trading system (i.e., the winning ratio, the payoff ratio, and the profit factor). An intelligent ensemble trading system with instance selection using GAs is then developed for investors in the stock market. An empirical study of the proposed model is conducted using 35 companies from the Dow Jones Industrial Average, the New York Stock Exchange, and the Nasdaq Stock Market from January, 2006 to December, 2016.

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Keywords: Instance selection; Genetic algorithms; Intelligent trading system; Ensemble trading system.

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1. Introduction

Data mining, or knowledge discovery in databases (KDD), is generally defined as the broad process of discovering hidden valuable knowledge or patterns in large amounts of data [5]. The process is composed of data preprocessing (i.e., data cleaning, integration, transformation, reduction, and discretization), modeling, data analysis, evaluation, and deployment [14]. Data preprocessing is one of the most important data mining processes since the data quality impacts the mining results. If poor data (or information) is coming into a process, unreliable and inconsistent results can be obtained; this is applicable to the concept of garbage in, garbage out (GIGO) in data-driven approaches, such as data mining, pattern recognition, and machine learning.

Data reduction techniques have generally used different approaches, such as feature selection, dimensionality reduction, and instance selection. In the literature, many related studies have shown promising results for data reduction using feature selection and dimensionality reduction when developing intelligent trading system [1, 4, 7, 12, 17]. For example, Zhong and Enke (2017) presented three dimensionality reduction techniques, including principal component analysis (PCA), fuzzy robust principal component analysis (FRPCA), and kernel-based principal component analysis (KPCA) to predict the daily direction of the S&P 500 Index ETF (SPY) return based on 60 financial and economic features. Other studies have also considered the use of technical indicators as features to an intelligent trading system [18, 19]. Chen et al. (2016) proposed a multi-factor time series model based on an adaptive network-based fuzzy inference system (ANFIS) for stock index forecasting. They considered stepwise regression to select technical indicators and then combined this with ANFIS to construct the forecasting model in the Taiwan and Hong Kong stock markets. Kim and Ahn (2012) proposed a new optimization model for artificial neural networks (ANNs) using GAs. It simultaneously optimizes four major architectural factors of ANNs, such as connection weights, the number of neurons in the hidden layer, feature subset selection, and feature transformation (i.e., discretization). Until now, the focus has been on selecting representative features or reducing dimensionality to obtain the same or higher accuracy (i.e., Up or Down prediction), rather than the original data set in stock markets.

However, data reduction carried out without instance selection for classification problems can lead to poor performance since the stock market is a complex system with noisy data. Thus, data preprocessing of instance selection is needed to achieve enhanced performance from learning algorithms [2]. One approach to instance selection is to calculate the distances to neighboring data points using a clustering algorithm (e.g., *k*-nearest neighbors). Another approach to instance selection is to choose the suitable instances (or objects) in the original data set to become the training data set for a learning algorithm. For example, a genetic algorithm (GA) approach to instance selection in ANNs is proposed in [8] to predict stock market movement. This result showed that if noisy and irrelevant instances are eliminated, not only does the classification accuracy increase, but the computational complexity can also be reduced. In particular, a GA is one of the most widely used algorithms for data reduction, such as feature selection, instance selection, and discretization [3, 7, 8, 9].

Nevertheless, from a practical point of view, trading performance is more important than classification accuracy when developing intelligent trading systems for the stock market; for instance, although classification accuracy is higher, trading performance might not be better if the trading system is evaluated using other factors, such as the winning ratio, the profit factor, the payoff ratio, and the number of trades [6, 13, 16]. Therefore, this study proposes a new approach to instance selection that uses GAs to define a set of target labels that can identify the buying and selling signals and then select instances based on the trading measures. Learning algorithms are then trained using the new reduced data set to develop an intelligent trading system. An empirical study of the proposed model is conducted using 35 stocks from the DJIA, NYSE, and Nasdaq Stock Market from January, 2006 to December, 2016. In addition, the results are compared to a conventional approach without instance selection.

2. An intelligent ensemble trading system with instance selection using genetic algorithms

An intelligent ensemble trading system with instance selection using GAs consists of three phases. In the first phase, instance selection using GAs is applied to produce a subset (i.e., instances) from the entire available data set, constructing a new training data set that is used for the learning algorithms. In the second phase, each supervised learning algorithm is trained using the new training data set. In the final phase, the intelligent ensemble trading system generates trading signals (i.e., the buy, hold, and sell signals) using the trading strategy based on the majority voting method.

2.1. Phase 1: Instance selection using genetic algorithms

A profitable trading system can be defined by the winning ratio (i.e., the ratio of the number of winning trades to the total number of trades, P), the profit factor (i.e., the ratio of the amount of winning trades divided by the amount of losing trades, P_f), and the payoff ratio (i.e., the ratio of average winning to average losing trade, P_{WL}) [6, 13, 16]. To calculate the expected gain of the trading systems, it is necessary to know how often the system wins (or loses) and the amount of the average winning (losing) trades. These measures are calculated as follows:

$$\overline{W} = \frac{\sum W}{N_W}, \ \overline{L} = \frac{\sum L}{N_L} \tag{1}$$

$$R_{WL} = \frac{\overline{W}}{\overline{N}} \tag{2}$$

$$P_f = \frac{\sum W}{\sum L} = \frac{N_W \times \overline{W}}{N_L \times \overline{L}} = \frac{N_W}{N - N_W} R_{WL} \tag{3}$$

$$P = \frac{N_w}{N} = \frac{1}{1 + \frac{R_{WL}}{P_f}} = \frac{P_f}{P_f + R_{WL}} \tag{4}$$

where $W(L)$ is the amount of the winning (losing) trade, with $N \ (= N_W + N_L)$ being the total number of trades. Eq. (4) is the profitability rule that relates the winning ratio to the profit factor and the payoff ratio [6]. To select instances, a profitable trading system is needed to identify market signals (i.e., buy, hold, sell, or no position). A GA is then used to identify points when a stock is bought and sold using the past stock closing price, as shown in Fig. 1.

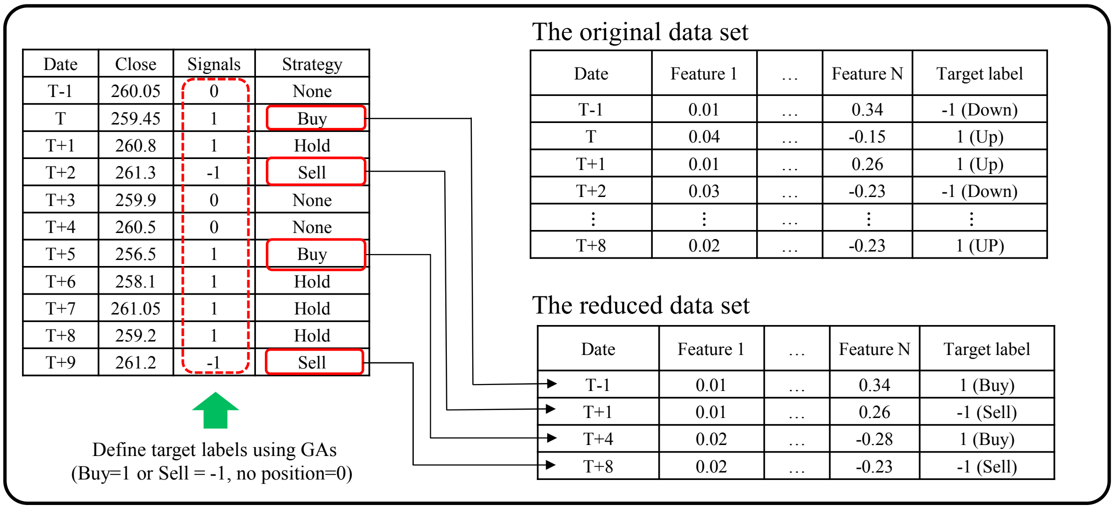

Fig. 1. Instance selection using GAs

For the defined fitness function, the objective function of the instance selection using GAs is calculated as follows:

$$\text{Maximize} \quad \frac{E(g)}{\bar{L}} \times No.\ trade = \frac{P \times \bar{W} - (1-P) \times \bar{L}}{\bar{L}} \times N \tag{5}$$

where $E(g)$ is the expected gain, with a profitable trading system generating a positive value. Eq. (5) highlights how a profitable trading system with a positive expectancy is maximized by multiplying by the number of trades (i.e., opportunities). In other words, Eq. (5) highlights what the trading system can be expected to earn, on average, for every dollar at risk. Also, constraints are used for statistical sampling, including the number of trades ($N > 30$), the winning ratio ($0.33 \leq P \leq 0.80$), and the payoff ratio ($0.25 \leq P_{WL} \leq 2.00$). These values are defined by Eq. (4) and the profit factor ($P_f \geq 1$) [6].

2.2. Phase 2: Trading signal generation by learning algorithms

For this phase, learning algorithms are applied to train patterns based on the new training data set reduced in phase 1. The learning algorithms used include the multinomial logistic regression (MLR), *k*-Nearest-Neighbors (*k*-NN), Native Bayes, and artificial neural networks (ANN) since these learning algorithms are popular classifiers. In order to retrieve the most similar cases and to calculate the distance, the Euclidean distance and the value *k* (= 5) were used for *k*-NN. For the ANN, a three layer (i.e., the input, hidden, output layer), fully connected back-propagation neural network (BPN) was used. A sigmoid function is used as an activation function with a learning rate (0.1) and momentum rate (0.1).

2.3. Phase 3: Ensemble trading strategy

According to the predicted value (buy: +1 or sell: -1) from each learning algorithm (i.e., classifiers), the majority voting method is used to calculate a trading signal (i.e., buy, hold, or sell) at time *t*. An ensemble trading strategy is described as follows:

IF $\sum C_i$ is greater than 0 (at time *t*) and no position (at time *t-1*), THEN buy signal
Else if $\sum C_i$ is greater than or equal 0 (at time *t*) and buy position (at time *t-1*), THEN hold
Else if $\sum C_i$ is less than 0 (at time *t*) and buy position (at time *t-1*), THEN sell signal
Else if $\sum C_i$ is less than 0 (at time *t*) and no position (at time *t-1*), THEN no position
Else no position (at time *t*) (i.e., $\sum C_i = 0$)

where C_i $(i = 1, \cdots, N)$ is i^{th} classifier (i.e., learning algorithm). This study used the classifiers (N=4) trained by the learning algorithms in Phase 2.

3. Experimental results

An empirical study of an intelligent ensemble trading system with the instance selection using GAs is conducted using the daily closing prices of 35 companies from the DJIA, NYSE, and Nasdaq Stock Market. The data was obtained from Yahoo Finance from January 2, 2006 to December 31, 2016. The datasets were divided into training (January 2, 2006 to December 31, 2015; 2266 instances) and testing (January 4, 2016 to December 30, 2016) sets. New reduced training data sets are generated for every year for each stock using the previously described GA instance selection procedure. The features (i.e., input variables) used in this study were 8 technical indicators, including the moving average convergence divergence (MACD), the price rate of Change (ROC), momentum, disparity (5), disparity (10), stochastic %K, stochastic %D, and moving average oscillator (MAO). The trading results are compared against traditional learning algorithms, such as *k*-nearest neighbors (*k-NN*), logistic regression, Naïve Bayes, artificial neural networks, and the ensemble classifier based on the majority voting method. For the modeling, a trading transaction cost of 0.1% was also considered.

To compare the trading performance of the intelligent trading systems with instance selection using GAs, the conventional approach without instance selection (i.e., the original data set) is conducted. The data set of the conventional approach is comprised of the same features, but the target labels are defined as Up (+1) or Down (-1) [7, 8, 9, 10, 11, 17]. From Table 1, all trading systems with instance selection using GAs outperform trading systems without instance selection for the testing data set. These results show that instance selection using GAs approach allows for better learning patterns compared to conventional approaches. These results also indicate that instance selection using GAs eliminates noisy and irrelevant instances from the original data sets, selecting better market signals to improve trading performance. In particular, the intelligent ensemble trading system with instance selection using GAs shows the best trading performance (average returns: 12.06%, standard deviation: 11.63) when compared with the other approaches. In addition, the ensemble trading system with the majority voting method helps to provide better trading performance.

Table 1. Average returns and standard deviation of trading results

No.	Classifier	The original data set	The reduced data set based on instance selection using GAs
1	*k*-nearest neighbors	-1.96% (13.43)	4.65% (13.39)
2	Logistic regression	6.24% (10.63)	8.75% (12.60)
3	Naïve Bayes	6.94% (8.65)	8.40% (12.70)
4	Neural networks	7.96% (12.63)	9.38% (11.70)
5	Ensemble	6.31% (7.44)	12.06% (11.63)

Tables 2-3 show trading performance of the ensemble trading systems according to various trading measures, including the number of instances (i.e., the number of samples), the winning ratio, the profit factor, the payoff ratio, and the number of trades. The intelligent ensemble trading system with instance selection using GAs produces larger profits compared to the conversional approach, illustrating that the training data set reduced by the instance selection using GA works effectively for learning algorithms. In addition, the ensemble trading system with instance selection using GAs obtains profit factors greater than 1 in 30 out 35 stocks. If the trading strategy is profitable, the profit factor is greater than 1, while a value less than 1 identifies a profitless trading strategy [6, 10, 15]. Furthermore, as shown in Tables 2-3, the proposed instance selection using GAs significantly reduces the data size (the average number of instances: 1141) for the learning algorithms, as compared with a conversional approach trained from all instances (i.e., 2266 instances).

4. Conclusions and future work

For this study, a novel instance selection using GAs is proposed for an intelligent ensemble trading system in the U.S. stock market. The results show that the proposed method can help to provide better profitability when compared to a conventional approach based on the original data set. The results also indicate that the training data set that was reduced based on instance selection using GAs helps the learning algorithms to train on patterns in the stock market, while the ensemble trading system can help to improve trading performance. These findings help to provide guidelines for developing an intelligent trading system when implementing instance selection approaches in the stock market. Nonetheless, it may be necessary to simulate different industry stocks, including defense contractors, drugs, and service industries before a stronger conclusion on robustness can be made. For further study, the intelligence ensemble trading system with instance selection using GAs could possibly be improved by allowing short selling of stocks. The model could also be applied to the futures market. In summary, both feature selection and instance selection should be considered in order to develop a more effective intelligence trading system.

Table 2. Trading results of the intelligent ensemble trading system with instance selection using GAs

No.	Stock ticker	No. instances	No. trades	Winning ratio	Average gain ($)	Average loss ($)	Payoff ratio	Profit factor	Return (%)
1	AAPL	1128	22	0.36	4.94	2.59	1.91	1.09	3.14
2	AXP	980	18	0.33	4.46	1.09	4.08	2.04	18.77
3	BA	1108	30	0.73	1.47	4.06	0.36	0.99	-0.14
4	BAC	1092	24	0.38	1.26	0.25	4.97	2.98	38.26
5	CAT	1088	28	0.54	2.94	1.79	1.64	1.89	27.86
6	CSCO	1080	18	0.44	0.88	0.49	1.80	1.44	8.07
7	CVX	1024	27	0.78	1.48	1.61	0.92	3.23	22.73
8	DD	1052	19	0.68	1.71	1.73	0.99	2.15	17.74
9	DIS	1080	18	0.28	5.28	1.40	3.77	1.45	7.75
10	GE	1156	20	0.70	0.31	0.68	0.46	1.07	0.91
11	GOOGL	1120	27	0.67	10.12	10.40	0.97	1.95	11.02
12	GS	1048	23	0.57	7.81	3.66	2.13	2.78	31.73
13	HD	1112	23	0.26	4.82	1.45	3.33	1.18	3.34
14	HPQ	1172	20	0.80	0.21	0.84	0.25	1.01	-0.13
15	IBM	1148	22	0.36	6.56	2.14	3.06	1.75	15.94
16	INTC	1152	27	0.26	1.39	0.70	1.99	0.70	-13.77
17	JNJ	1128	27	0.74	0.99	1.79	0.55	1.57	7.12
18	JPM	1140	21	0.43	3.15	1.11	2.84	2.13	21.81
19	KO	1160	27	0.74	0.33	0.43	0.78	2.22	8.63
20	LOW	1212	32	0.56	1.02	1.43	0.71	0.92	-2.27
21	MCD	1180	28	0.64	1.19	2.37	0.50	0.90	-2.06
22	MMM	1168	14	0.71	1.92	3.57	0.54	1.35	3.43
23	MRK	1224	31	0.74	0.75	0.70	1.07	3.08	20.87
24	MSFT	1208	29	0.76	0.97	0.97	1.00	3.14	24.34
25	NKE	1216	14	0.64	1.27	0.70	1.82	3.28	12.36
26	PEP	1252	21	0.76	0.80	1.81	0.44	1.42	3.91
27	PG	1208	24	0.79	0.84	0.94	0.89	3.38	13.86
28	T	1148	23	0.70	0.35	0.54	0.64	1.47	5.42
29	TRV	1144	25	0.60	1.44	1.12	1.28	1.92	9.27
30	UNH	1212	26	0.69	1.91	1.37	1.39	3.13	18.67
31	UTX	1136	22	0.59	1.63	0.85	1.91	2.76	13.64
32	VZ	1144	18	0.56	0.62	0.79	0.78	0.98	-0.35
33	WMT	1168	32	0.78	0.82	0.44	1.88	6.71	25.72
34	XOM	1176	16	0.75	1.14	1.75	0.65	1.96	8.62
35	YHOO	1176	26	0.88	0.68	0.73	0.94	7.21	35.81
Average		1141	23.53	0.61	2.21	1.67	1.52	2.21	12.06

Table 3. Trading results of the intelligent ensemble trading system without instance selection (the conversional approach)

No.	Stock ticker	No. trades	Win%	Average gain ($)	Average loss ($)	Payoff ratio	Profit factor	Return (%)
1	AAPL	11	0.55	2.59	2.48	1.05	1.25	3.03
2	AXP	17	0.71	1.11	3.00	0.37	0.89	-2.63
3	BA	11	0.73	5.84	11.86	0.49	1.31	7.93
4	BAC	23	0.57	0.31	0.46	0.68	0.88	-3.38
5	CAT	22	0.64	1.72	2.11	0.81	1.42	10.44
6	CSCO	18	0.33	1.17	0.52	2.26	1.13	3.08
7	CVX	15	0.67	2.73	2.21	1.24	2.47	17.64
8	DD	31	0.74	0.86	1.84	0.469	1.35	8.02
9	DIS	10	0.60	1.82	2.76	0.66	0.99	-0.11
10	GE	11	0.27	1.50	0.41	3.64	1.36	3.99
11	GOOGL	17	0.53	24.98	17.46	1.43	1.61	10.63
12	GS	14	0.71	4.39	6.72	0.65	1.63	9.33
13	HD	15	0.40	3.63	2.41	1.51	1.00	0.08
14	HPQ	19	0.79	0.43	1.04	0.41	1.55	18.80
15	IBM	13	0.77	3.73	3.95	0.94	3.15	17.89
16	INTC	10	0.50	1.15	0.30	3.85	3.85	12.22
17	JNJ	9	0.67	3.26	3.09	1.05	2.11	10.05
18	JPM	23	0.91	0.83	2.41	0.35	3.62	18.60
19	KO	13	0.23	0.97	0.58	1.68	0.51	-7.26
20	LOW	17	0.35	3.26	2.00	1.63	0.89	-3.36
21	MCD	9	0.67	2.37	3.41	0.70	1.39	3.47
22	MMM	10	0.60	1.74	1.82	0.96	1.43	2.20
23	MRK	17	0.59	0.95	0.63	1.50	2.14	9.58
24	MSFT	18	0.78	1.36	1.44	0.94	3.31	22.30
25	NKE	30	0.70	0.67	1.46	0.46	1.06	1.37
26	PEP	12	0.25	1.81	1.42	1.28	0.43	-7.98
27	PG	28	0.71	0.73	1.06	0.69	1.72	7.86
28	T	14	0.79	0.65	1.80	0.36	1.32	5.23
29	TRV	22	0.59	2.25	1.08	2.09	3.02	16.78
30	UNH	16	0.75	1.79	2.94	0.61	1.83	8.20
31	UTX	20	0.70	1.23	2.13	0.58	1.35	4.65
32	VZ	9	0.78	1.02	1.90	0.54	1.88	7.40
33	WMT	23	0.61	1.08	1.62	0.66	1.03	0.80
34	XOM	21	0.71	0.83	1.79	0.46	1.16	2.22
35	YHOO	25	0.52	0.76	0.78	0.97	1.05	1.57
Average		16.94	0.61	2.44	2.65	1.08	1.63	6.31

Appendix A. Stock Ticker Symbols

The Dow Jones Industrial Average (DJIA) is recognized as a leading index and contains 30 of the most liquid securities in the U.S. stock market. However, of the 30 stocks in the DJIA, the component company Visa has been excluded for analysis since it provides fewer data points compared to the other stocks in the index. The remaining 6 stocks in the study were selected from either the New York Stock Exchange (NYSE) or the Nasdaq Stock Market since they are also well-known companies with liquid and actively traded stocks.

No.	Stock	Ticker	No.	Stock	Ticker	No.	Stock	Ticker
1	Apple	AAPL	13	The Home Depot	HD	25	Nike	NKE
2	American Express	AXP	14	Hewlett–Packard	HPQ	26	PepsiCo	PEP
3	Boeing	BA	15	IBM	IBM	27	Procter & Gamble	PG
4	Bank of American	BAC	16	Intel	INTC	28	AT&T	T
5	Caterpillar	CAT	17	Johnson & Johnson	JNJ	29	Travelers	TRV
6	Cisco Systems	CSCO	18	JPMorgan Chase	JPM	30	UnitedHealth Group	UNH
7	Chevron	CVX	19	Coca-Cola	KO	31	United Technologies	UTX
8	DuPont	DD	20	Lowe's	LOW	32	Verizon	VZ
9	Walt Disney	DIS	21	McDonalds	MCD	33	Wal-Mart	WMT
10	General Electric	GE	22	3M	MMM	34	ExxonMobil	XOM
11	Alphabet	GOOGL	23	Merck	MRK	35	Yahoo	YHOO
12	Goldman Sachs	GS	24	Microsoft	MSFT			

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