

Analysis of Executive Transaction Characteristics Based on Machine Learning Cross-Validation

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Abstract:

This paper adopts the machine learning cross-validation method, selects the transaction data of the increase and reduction of the stock holdings of executives of A-share listed companies from 2008 to 2018, and conduct 10 cross-checks on the data set to analyze the characteristics of executive transactions. On this basis, the accuracy of the model was further tested with 2019 data. The research found that: (1) among the four models of machine learning, the decision tree model is more prominent than regression analysis, random forest model and support vector machine model in terms of recall, precision, accuracy and F1 measurement. And the data forecasting ability is the best, which can accurately predict the trading behavior of executives; (2) the stock market environment of listed companies has been constantly changing, and the cumulative excess returns of executives' share holding transactions have shown an inverted V shape, that is, the short-term return is negative and the long-term return is positive; (3) the short-term stock return is always negative before and after the executive share reduction transaction.

Keywords: *Machine learning, Executive behavior, Cross-validation, Transaction characteristics, Model backtesting.*

I. RESEARCH BACKGROUND

1.1 Literature review

Since the implementation of the split share structure policy, tradable shares have gradually acquired the right to circulate. In this context, China's stock market has officially entered the era of large circulation, and equity trading events occur frequently. In recent years, domestic scholars have carried out a lot of research on executive trading behavior, and have formed systematic literature in many aspects. Zhou Haowen, Li Jijian and Liu Tingting believe that

senior executives of listed companies(including members of the board of directors, senior managers and supervisors) can grasp the current valuation level and future development trend of the company at the first time through daily operation and management on characteristics of executives and corporate performance is the key research direction in the field of corporate governance, which is specifically reflected in whether executives play an important role in corporate decision-making. If the personal characteristics of executives can be accurately predicted, it will play an important role in corporate governance ^[2]. Based on the perspective of external investors, Xu Yingpeng and Guo Xuemeng pointed out that the transaction behavior of enterprise executives can promote the M & a performance of enterprises, and then realize the probability of increasing returns and reducing risks of external investors ^[3]. From the perspective of information transparency, Zeng Qingsheng made a research on the behavior of senior executives and their relatives in transacting company stocks. The results show that the smaller the company size and the lower the information transparency, the higher the investment profit for executives and their relatives; the larger the company size and the higher the information transparency, the investment profit is not significant. Therefore, it is pointed out that the bad trading behaviors of senior management can easily affect the improvement of the information quality of listed companies, and it is necessary to strengthen the supervision and review to reduce the bad trading behaviors of the company's senior management ^[4]. Zeng Yamin and others studied the influence of executive short-term trading, income difference of different executives and explanation reasons of executive short-term trading on the characteristics of executive trading, found that the trading behavior of executives of listed companies can effectively affect the acquisition of vested interests, among which supervisors have the largest profit margin due to short-term trading ^[5]. At the same time, Luo Qiao and Wang Guipu conducted in-depth research on the data related to the information disclosure of senior executives by using the event research method. The study found that the information released by the company's executives on the day of stock trading in the secondary market did not have value content. With the passage of time, the company's executives will correctly predict the stock price trend in the medium-term stage, which has a certain positive effect on medium and long-term investment ^[6]. With the end of 2011, most of China's non tradable shares have been lifted, and insider trading has gradually become the norm for executives of listed companies to make profits. In this context, Zhu Chafen, Chen Chao, and Zhou Luhai analyzed the characteristics of the company executives' insider trading, delayed disclosure, and insider trading based on the transaction data of senior executives of listed companies on the Shanghai Stock Exchange ^[7]. Li Huan and Luo Ting studied the self-interest motivation of executives with the help of A-share performance prediction and executive trading data of listed companies. It turns out that executives will try to increase stock prices through the release of performance company performance forecasts, thereby increasing their own stock profits; when executives buy stocks, they will release news that is not conducive to the company's

operations to reduce stock purchase costs; when executives prepare to sell stocks, they will work hard to promote the company's performance in order to raise the stock price to obtain excess profits^[8]. Li Peigong studied insider trading behavior of delisted companies. The results show that the majority shareholders of the company will oversold their stocks in the first two years of delisting through instant messaging, while most of the executives of the company show optimistic attitude towards the company, so that they will oversell stocks only in the year of delisting^[9]. Malmendier and others believe that executives will influence the development of enterprises (production and sales scale, enterprise efficiency, financial status, customer service maintenance, etc.) through their personal skills, life experience, career experience, education experience and other factors^[10].

Based on the views of the above scholars, it can be seen that the top executives will have adverse effects due to the influence of external or internal factors. Therefore, it is necessary to use new statistical tools to update the characteristics of executive Trading^[11]. In statistical machine science, the Cross-Validation method is to segment the data set for many times and repeat experiments, and then predict the error of the data. Because different segmentation methods will make the number of samples in all data sets different, Yang Jing, Wang Ruibo and Li Jihong constructed balanced RHS (repeated half sampling) Cross-Validation, which greatly reduced the variance of generalization error estimation and effectively improved the stability^[12]. He Fangchao and others pointed out that the Cross-Validation results of hypothesis stability condition and consistent hypothesis stability condition in machine learning algorithm supplement the conclusion of lower bound of stability condition of learning algorithm^[13]. With the help of semi supervised classification method, scholar Zhao Jianhua realized deep-seated mining of samples by using the marker with the smallest error of SVM classifier as the final marker^[14]. According to this, some scholars use Cross-Validation method to study variables such as financial data of listed companies^[15]. Li Hongmei and Wu Xizhi conducted cross-validation on the longitudinal data of protein contained in milk, and finally verified that the efficiency of Cross-Validation method based on machine learning is higher than that of traditional statistical tools, whether it is long-term prediction or short-term prediction^[16].

1.2 Research purpose

After the reform and opening up, China has successfully transited from a highly centralized planned economic system to a socialist market economy with Chinese characteristics. With the gradual establishment of China's market economic system, the economic environment appears obvious fluctuations. However, the fluctuation of economic environment may greatly affect the transaction characteristics and corporate performance of executives. It is difficult to obtain a reliable prediction model under the fluctuation of economic environment by using linear fitting

model in the past ^[17]. At the same time, the existing literature found that the nonlinear relationship between the personal characteristics of executives and corporate performance will have interaction, which means that the traditional linear fitting model has been difficult to clearly and clearly comb the complex relationship between variables ^[18]. According to the business guidelines for the management of changes in shares of senior executives of Shanghai Stock Exchange and Shenzhen Stock Exchange, when the shares of the company held by senior managers, including members of the board of directors, senior managers and supervisors, should be filled in and disclosed on the securities trading website within 2 trading days from the date of the act. But this kind of practice will further lead to a problem. Although executives disclose their trading information in the regulatory authorities, how can ordinary investors achieve investment benefits through such disclosure? In view of the defects of the traditional statistical methods, it is impossible to accurately locate this kind of data. Therefore, this paper uses a more advanced machine learning model to predict the impact of a single security, and then through the prediction results to imitate executives to carry out stock trading or reverse operation, in order to make ordinary investors drive investment through executive trading events.

II. RESEARCH METHODS AND DATA SOURCES

2.1 Research methods

In machine learning, it is usually impossible to use all the data for model training; otherwise the model will not have reliable verification data set, which will affect the prediction and evaluation effect of the model. Usually, in order to ensure the validity of the data and improve the evaluation effect of the model, researchers will divide the data set into two parts, one is used to train the data to form the training set, and the other is used to verify the model effect. This method is simple and direct, but it also has two disadvantages. One is that only part of the data is used for model training, which leads to a big difference between the final training model effect and the model effect verified by a large number of data. The second is that the parameter selection and the final model are extremely dependent on the partition method of these two parts of data. Once there is a problem with the data partition method, it is very likely that the best parameters and model can not be selected.

Constrained by these two drawbacks, the academic community proposed a Cross-Validation method. There are two Cross-Validation methods: LOOCV and K-Fold Cross-Validation. Among them, LOOCV method also has two data sets: training set and test set. However, there is only one data in the test set of LOOCV method, and other data are in the training set for training model and parameter adjustment. In the LOOCV method, the data in

the test set and the training set are not fixed, but each time a test is made, a data is taken from all the data as a test element. Therefore, the number of training times of each model is the number of data in the data set. Assuming that there are N data sets in the current data set, then the number of data in the training set in the LOOCV method is $N-1$. Finally, the number of repetitions of training steps is N times. The specific calculation formula is as follows (1). The advantage of LOOCV method is that the data is not affected by the partition of test set and training set, which greatly reduces the validation bias of the model. But its disadvantage is that the calculation amount is too large and the calculation cost is high. So some scholars put forward formula (2) to reduce the calculation cost. Where is the \hat{y}_i fitting i -th value and the h_i represents the influence effect.

$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^n MSE_i \quad (1)$$

$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^n \left(\frac{y_i - \hat{y}_i}{1 - h_i} \right)^2 \quad (2)$$

In the test set of K-Fold Cross-Validation method, the number of data is the value of K , and the calculation formula is formula (3). For example, if $k = 4$, then the model will be cross validated by four fold. The specific steps are as follows: firstly, divide all the data into four parts; secondly, take out one of them each time, which can't be repeated. Use the other three as the training model of the training set, and then calculate the model's performance on the test set; thirdly, take the average of MSE_i obtained from 4 tests to obtain MSE , which is used to measure the test error. In the K-Fold Cross-Validation method, the value of K is very important, not too large or too small. According to experience, the K value is generally determined as 5 or 10.

$$CV_{(k)} = \frac{1}{k} \sum_{i=1}^k MSE_i \quad (3)$$

When the problem of classification is encountered, equation (4) can be used to measure the test error of Cross-Validation method. The number of classification errors of the i -th model on the i -th test set is Err_i .

$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^n Err_i \quad (4)$$

The transaction characteristics of executives in this article are mainly divided into two types: increase and reduction of shares, and the K value is determined to be 10.

2.2 Data sources

This article mainly uses a web crawler program to obtain regulatory data published by the Shenzhen Stock Exchange. The filtered data is the data of A-share listed companies from 2008 to 2018. Due to research needs, the data only retains the types of stocks traded in the secondary market, and a total of 10325 valid data were screened out. Combined with the stock increase and reduction data of important shareholders in the wind database, and field processing, a total of 24 data fields are obtained.

III. VARIABLE DESCRIPTION AND MODEL CONSTRUCTION

3.1 Variable definition and description

3.1.1 Explained variable

This article mainly studies the short-selling strategies of executives after increasing or decreasing their holdings. As there is no stock short-selling mechanism in China for the time being, the short-selling method in margin trading and securities lending can only be adopted. At present, the annual rate of the mainstream margin trading is about 10.5%, that is to say, if short selling is used, the profit margin will only be made if the reduction is greater than 0.8%. Taking into account the commission cost, it is more appropriate when the return on short-selling securities reaches 1%. This paper defines a period of time as 20 trading days. If the return is less than or equal to -0.01, it is marked as 1, otherwise it is marked as 0. Finally, 1745 records marked as 1 and 2174 records marked as 0 are obtained.

3.1.2 Explain variables

Firstly, the number of traders who increase or reduction their shareholding ratio on the same day. Consolidate the number of events in which executives increase or reduction their holdings in a trading day. If there are more than one executives who simultaneously increase or reduction their holdings in a single day, the variable is selected as 1, otherwise it is selected as 0. Secondly, the transaction behavior of senior management increasing or decreasing holdings. Differentiated trading behavior will bring different short-term returns. Generally speaking, the trading behaviors of executives of listed companies can be divided into two types, namely follow-up trading and reverse trading. Follow-up trading can transmit a lot of enterprise information. The main purpose of this paper is to investigate whether the senior executives

have the same trading behavior 10 days before the increase or reduction of holdings. If there is, the value is 1, if not, the value is 0. Thirdly, executives increase or reduction the scale of transactions. The scale of transactions for increasing or decreasing shares is different, and the impacts are also different. Compared with small-scale transactions, large-scale transactions bring higher excess returns. Fourthly, Company valuation information. The valuation information of listed companies can reflect the timing of executives' increase or reduction in their holdings, which is mainly expressed by indicators such as market-sales ratio, price-earnings ratio, and price-to-book ratio. The market-sales ratio is mainly used to reflect the company's operating income and can reflect the stable performance. The price-earnings ratio is suitable for manufacturing and service industries with less cyclicity, and the price-to-book ratio is suitable for cyclical companies to value. The executives of listed companies have a strong advantage in identifying company valuation deviations in predicting the company's performance prospects. By comparing the performance of the company in the previous period, that is, the growth rate of net assets and the rate of return on total assets, the executives of listed companies can predict the performance of the company in the next stage, and then make transactions to increase or reduction shareholding. Therefore, the company's profitability, capital structure, solvency, and operating capacity can be used as explanatory variables. The definition and description of each variable are shown in Table I.

TABLE I. Definition and Description of Each Variable

Variable definitions		Description
Explained variable	Senior management's increase or reduction in Holdings	If the income of 20 trading days is ≤ -0.01 , it is recorded as 1, otherwise it is recorded as 0.
Explanatory variables	Increase or reduction of the number of transactions held by senior executives	If the number of executives who have increased or reduced their holdings at the same time in a single day exceeds 1, take 1, otherwise take 0
	Transactional behavior of executives	If an executive has a follow-up transaction, select 1, but not 0. If the average income in the first 10 days of the increase or reduction of holdings is a negative number, the executive chooses 1 when they choose to increase their holdings and 0 when they choose to reduce their holdings; if the average income of the 10 days before the increase or reduction in holdings is a positive number, When executives choose to reduce their shareholding, take 1 and when they choose to increase their shareholding, take 0.
	Executives increase	Expressed by the excess returns of listed companies.

	or reduction the scale of transactions	
	Company valuation information	It is expressed by indicators such as market-sales ratio, price-earnings ratio, and price-to-book ratio.

3.2 Model construction

The data related to the above variables are sorted into a data set, and the regression analysis (Logistic) of the machine learning model, the random forest model, the decision tree model and the support vector machine model (SVM) are applied respectively, and the data set is subjected to 10 10-fold cross-checks. The evaluation indicators are mainly recall rate, precision rate, accuracy and F1 measurement. The final evaluation results of different models are shown in Table II.

Table II. Evaluation Results of Regression Analysis, Random Forest Model, Decision Tree Model and Support Vector Machine Model

Model	Recall rate	Precision rate	Accuracy rate	F1 measurement
Logistic	0.1683	0.5130	0.5534	0.2391
Random forest	0.0959	0.5578	0.5502	0.1495
Decision tree	0.2378	0.5537	0.5555	0.3047
SVM	0.1642	0.5021	0.5523	0.2344

Note: 1. Logistic regression and SVM support vector machines both use the L1 paradigm for dimensionality reduction; 2. Random forest has been tested with about 200 subtrees with good results; 3. The final parameter of the decision tree with the best performance is the largest tree The depth is 3 layers, and the minimum number of leaf nodes is 5.

It can be seen from the data in Table 2: In terms of recall rate, the recall rate of the random forest model is slightly lower, less than 9.6%, and the recall rate of other models exceeds 16%. Among them, the decision tree model has the highest recall rate. It is 23.78%; in terms of precision, the precision of random forest model and decision tree model are both high, exceeding 55%; in terms of accuracy, the four models are all stable above 55%; in terms of F1 measurement, decision tree The value of the model is the largest, exceeding 30%, and the value of the random forest model is the smallest, less than 15%. From a comprehensive comparison, the decision tree model performs better in recall, precision, accuracy, and F1 measurement, and is the most suitable model.

Based on the machine learning cross-validation method, a decision tree model is constructed to specifically analyze the characteristics of executive transactions, and the result is

as shown in formula (5).

$$tree = DecisionTreeClassifier(random_stste = 2018) \tag{5}$$

The scoring function is further constructed, and the 10-Fold Cross-Validation is used for verification scoring.

```
def muti_score(model)
    warnings.filterwarning(ignore)
    accuracy = cross_val_score(model, df_X, df_y, scoring =`accuracy`, cv10)
    precision = cross_val_score(model, df_X, df_y, scoring =`precision`, cv10)
    recall = cross_val_score(model, df_X, df_y, scoring =`recall`, cv10)
    f1_score = cross_val_score(model, df_X, df_y, scoring =`f1`, cv10)
    auc = cross_val_score(model, df_X, df_y, scoring =`roc_auc`, cv10)
    print("accuracy:",accuracy.mean())
    pArint(" precision ",precision.mean())
    print(" Recall: ",recall.mean())
    print(" F1_score: ",f1_score.mean())
    print(" AUC :",auc.mean())
```

3.3 Abnormal backtesting

In order to test the significance of the average abnormal return, this paper sets the test time to [0,20] and [0,60], and selects the T1 statistic to test the model. Since the sample size of the two time periods is small, the t test is used for them. Table III shows the results of the obtained transaction inspection of the increase or reduction of executive shares.

TABLE III. Parameters of the Inspection Results of the Increase or Reduction of the Shares Held by Executives

	Inspection type	P	Statistics	time limit
Increase	t test	0.000015	-7.01	[0,20]
Increase	t test	0.000012	-9.71	[0,60]
Reduction	t test	0.000018	-20.53	[0,20]
Reduction	t test	0.000019	-32	[0,60]

As far as the increase transaction is concerned, it can be seen from the test results of the top

two rows of Table 3 that the P values are 0.000015 and 0.000012 respectively in the period of [0,20] and [1,60], which are far less than the significance level of 0.01. This means that the average abnormal returns in the short-term 20 days and the long-term 60 days are significant. The results of unit test on the increase trading of two date ranges show that the statistical values are - 7.01 and - 9.71 respectively. This shows that the average abnormal return does not bring significant positive returns after the increase of senior executives.

As far as the reduction transaction is concerned, from the test results of the reduction transaction of senior executives' shares in the last two rows of Table 3, it can be seen that during the period of [0,20] and [1,60], P values are 0.000018 and 0.000019 respectively, which are far less than the significance level of 0.01. This means that the average abnormal returns in the short-term 20 days and the long-term 60 days are significant after the executive share reduction transaction. Then, the unit test of the reduction transactions in the two date ranges shows that the statistical values are - 20.53 and - 32, respectively. This shows that the average abnormal return of executives is significantly negative, which is consistent with the general perception of investors.

IV. RESULTS ANALYSIS AND BACKTESTING

4.1 Result analysis

In order to verify the transaction characteristics of executives, the decision tree model is used to train all variable data sets of 24 data fields, and the final output of the decision tree is shown in Figure 1.

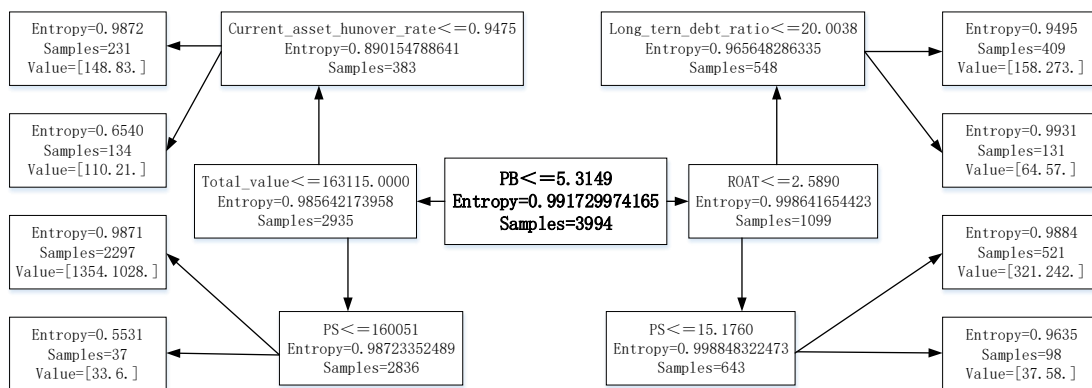


Figure 1: Decision Tree Model

As can be seen from Figure 1: firstly, when the root node value is 5.27, the price to net ratio is judged from the return on total assets and the total market value. The rate of return on total assets can reflect the company's profitability in the previous stage. According to the rate of

return on total assets of listed companies, and combined with the current operation of the company, the top executives will make profit expectations. This profit expectation contains a lot of important information, which can provide a reference for executives to increase or reduce their holdings. The size of the total market value can show the degree of attention of listed companies, and then affect the transparency and speed of information dissemination. Secondly, the effect of short-term variables on the prediction effect is less affected by the short-term variables, but more affected by the long-term variables of the company's financial status after the stock increase or reduction event. Thirdly, the nodes in the third layer include market sales rate, current assets turnover rate and long-term debt ratio. The three indicators reflect the performance growth, operating capacity and liabilities of enterprises respectively. When the market sales ratio of the listed company is less than 16, the return of the enterprise is probably negative; when the turnover rate of the current assets of the listed company is small, it is easier to produce the income less than - 0.01; in the long-term debt ratio of the listed company is less than 20%, the probability of misjudgment is large, so it is necessary to add more nodes to improve the difference of senior executives' trading behavior. Generally speaking, when the return on total assets, valuation and asset liability ratio of listed companies are high, the increase or reduction of senior executives' shares will bring positive returns to the enterprise; when the market value is small, the valuation of price to book ratio is moderate and the market efficiency is low, the stock increase and reduction transaction behavior of senior executives will produce negative returns.

4.2 Model backtesting

The paper uses the Cross-Validation method of machine learning to model the transaction events of the increase and reduction of senior executives' shares in listed companies. The analysis shows that the decision tree model has better prediction ability. However, in the real market, whether the forecast results can be converted into the actual economic benefits of listed companies is the most important issue for investors. Therefore, this paper continues to test the transaction of the increase and reduction of senior executives' shares using decision tree model, and tests the stability and actual profitability of the model.

Firstly, the training set data of A-share listed companies from 2008 to 2018 are trained to obtain the decision tree model.

Secondly, input the transaction data of the increase and reduction of senior management shares of Listed Companies in the whole year of 2019 into the model, and conduct transactions according to the following investment strategies. (1) When the prediction result of the model is recorded as 0, no change is needed; (2) when the prediction result of the model is recorded as 1,

it is necessary to sell the security quickly; when the quantity result is 1 and 20 stocks are held, it is necessary to buy and close the position on the trading day. During the position period, if the purchase price of the purchased securities is 10% of Xiaoyu's purchase price, stop loss is not required, and stop loss is required in time if the purchase price is greater than 10%.

The first and last transactions of this strategy occurred on January 1, 2019 and December 31, 2019, respectively. In this stage, the initial capital of the transaction of increasing or decreasing the shares of senior executives is 50000. Without considering the transaction cost of share capital, assuming that the annualized interest rate of securities is 8.4%, the change of strategic capital is plotted, as shown in Figure 2. As can be seen from Figure 2, although the funds for this strategy fluctuated and fell to about 42000 in about 110 days, it showed an overall upward trend. The capital has reached 66000 by December 2019, which shows that this strategy can make executives obtain higher profits in the middle and later stages.

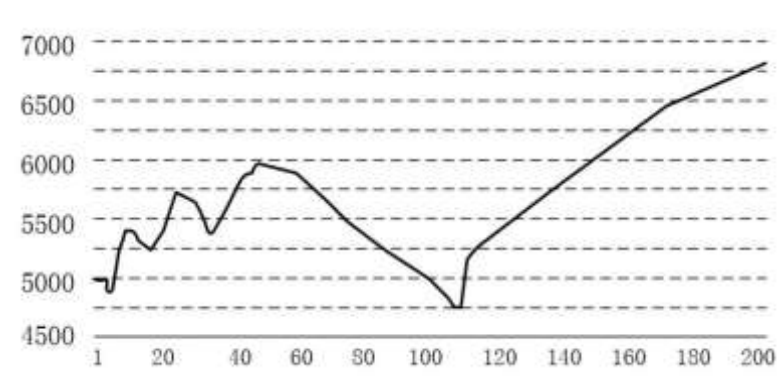


Figure 2: Changes in Strategic Funds

Subsequently, in the model, the backtest results of the stock increase and reduction transactions of the listed company's executives from the beginning of 2019 to the end of the year were calculated and plotted in Table IV. It can be seen from Table 4 that from the beginning of 2019 to the end of the year, the market return rate dropped by 3.87%. At this time, the final return rate of this strategy is 9.75%, the excess return obtained in the volatile market is 14.62%, and the maximum drawdown is 5.43%, indicating that this strategy has better risk control capabilities. In the 237 open trading days, a total of 66 trading signals were generated. The average number of trading signal generation days was 3.59 days, with a total of 12 stop losses, which is a low-frequency strategy. The total profit of this strategy is 14,958, the total loss is 9037, the profit-loss ratio is 1.65, and the profitability is at a medium level. In general, this strategy has moderate returns and strong risk control capabilities, making it more suitable for falling or volatile securities trading markets.

Table IV. Model Backtesting Results

Rate of return	9.75%	Total number of positions opened	237	Profit times	37	Number of losses	29
Over the same period market return	3.87%	Number of trading signals/day	3.59	Profit amount	14958	Loss amount	9037
Excess income	14.62%	Stop loss times	12	Average profit per transaction	404.3	Average loss per transaction	311.6
Maximum drawdown	5.43%	Normal closing	54	Profit-loss ratio	1.65		

V. CONCUSION AND SUGGESTION

5.1 Conclusion

To sum up, this paper analyzes the trading characteristics of the increase and reduction of senior executives' shares based on the Cross-Validation method of machine learning, compares the four models of machine learning, and further inputs the transaction data of top management shares of listed companies in 2019 into the selected model to backtest the accuracy of the model. The results show that: (1) among the four machine learning models, the decision tree model has the best performance in recall, precision, accuracy and F1 measurement, and has the best prediction ability. It can accurately predict the increase or reduction of senior executives' shares in listed companies, and help enterprises obtain stable investment returns; (2) the stock market environment of listed companies has been in constant change, the accumulated excess return of the executive stock increase transaction presents an inverted V shape, which can only make the enterprise obtain negative income in the short term, and can obtain positive return in the long term; (3) the short-term stocks before and after the reduction of senior executives' shares are not sensitive to the announcement date and are always negative returns, but the cumulative average returns show a straight-line decline before and after the event announcement date.

5.2 Suggestion

With the changing environment of China's stock market, investors are also making progress. However, from the above analysis, in order to improve the impact of machine learning Cross-Validation on investors' investment efficiency, the focus should be on the implementation of differentiated new and old media disclosure carrier system, the establishment of risk early warning mechanism and other aspects of regulation.

Implement the differentiated new and old media disclosure carrier system. At present, the

media disclosure channels formulated by China Securities Regulatory Commission mainly include paper media and internet, which have become two main means for listed companies to keep pace with each other in information disclosure. Therefore, the relevant regulatory authorities can make differentiated arrangements for different listed companies. First of all, for the listed companies with excellent information disclosure records, the mandatory disclosure of paper media can be cancelled, allowing them to freely choose between the network and paper media; for the listed companies with poor information disclosure, it is still necessary to conduct dual channel disclosure. This differential arrangement helps to encourage enterprises to actively disclose information, and can also reduce the cost of information disclosure through differential adjustment.

Establish risk early warning mechanism. Specifically, risk early warning mechanism needs to meet the following functions: first, information collection function. That is to collect the differentiated transaction information disclosed by the executives of listed companies, and through the analysis and comparison of the information, then realize the early warning function. Second, detection function. Based on the function of information collection, a horizontal comparison should be made between the transaction information disclosed by senior executives and listed companies in the same situation. If the gap is large, it is necessary to detect the abnormality of information disclosure and give warning in time. Third, prediction function. The history of information disclosure of executives in listed companies can warn executives and regulators of hidden problems in information disclosure, so as to reduce the failure of disclosure as soon as possible. Fourth, diagnostic function. In other words, it is necessary to provide some improvement suggestions for the information disclosure of senior executives of listed companies, and formulate reasonable reform measures to prevent the failure of information disclosure.

Improve the prior regulatory framework of insider trading. Firstly, according to different types of insider information of executives, different regulatory methods should be adopted to classify the regulatory objects. The senior executives who legally obtain trading information can conduct insider trading by means of covert trading. This kind of way is not easy to investigate and deal with, and it is more harmful. Therefore, it is necessary to monitor the traditional executives' insider dealers, such as the implementation of insider registration management system to regulate the bad trading behavior of executives and other insider traders. Second, the longer the executive insider trading time span, the more conducive to their "safe" securities trading, and then obtain excess benefits, the greater the harm to the financial environment. Therefore, the prior regulatory framework should be improved as soon as possible. Shorten the period from insider trading to final public disclosure, the time span of insider trading for executives should be reduced as far as possible, so as to reduce the harm of

insider trading. Specifically, it can be regulated from the following aspects: (1) requiring the executives of listed companies to voluntarily declare the number and changes of shareholding; (2) forbidding internal traders to buy and sell the company's stocks; (3) filling the company with the benefits obtained from short-term trading. Through such measures, insider trading by executives of listed companies can be prevented to a certain extent and the possibility of market manipulation by executives in the form of insider trading can be reduced.

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