# Trading strategy based on investment diversification technical analysis model

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Abstract: This paper takes gold and bitcoin as research objects and develops a model for traders. In this period, we established a multivariate quantitative technical analysis model of investment, selected 6 technical indicators with low correlation MA, MACD, BOLL, RSI, KDJ and Stoch RSI as evaluation indicators of trading intentions, and used the fuzzy evaluation model to combine the trading intentions of the 6 indicators to obtain the final daily trading intentions score. Combined with the trading intention score and risk tolerance coefficient of the day to adjust the asset allocation, the investment trading model proposed in this paper can provide support for relevant practitioners and has practical application significance.

**Keywords:** Investment Multivariate Quantitative Technical Analysis Model, Fuzzy Evaluation Model, Asset Allocation

#### 1. Introduction

With the improvement of people's living standards, we have more and more spare money in our lives. At this time, there will be more and more people choosing to invest, which requires that we should build a more scientific and objective portfolio model that makes the highest rate of return and the least risk. Market traders earn profits by buying and selling volatile assets frequently. Two popular assets in the market are gold and bitcoin. There is usually a commission for each purchase and sale. At present, many relevant practitioners need to complete transaction related decisions through the transaction information of the day, and determine the transaction intention. At the same time, they also need some indicators to measure whether the strategy provided by the model is the best. Therefore, this paper takes the gold and bitcoin prices from November 2016 to October 2021 as the research object. First, comprehensive evaluation indicators are used to establish a diversified quantitative model of investment, Secondly, the modeling strategy provided by the model is measured by the transaction success rate, and finally the availability of the model is proved by the risk coefficient.

# 2. The best strategy based on price data up to that day

## 2.1. Synthesize evaluation indicators to determine transaction intentions

In order to get the best portfolio, we need to determine the degree of trading intention, that is, when to buy assets and when to sell them for the greatest gain [1]. Combining common technical indicators and available data, we selected the indicators that affect volatile assets are MA, MACD, BOLL, RSI, KDJ, Stoch RSI. Using the nature of the above indicators to determine buying and selling points.

# (1) Determination of evaluation factors

We selected six factors as evaluation factors reflecting the intention to trade, and the set of evaluation factors is as follows:

$$X = \{x_1, x_2, x_3, x_4, x_5, x_6\} = \{MA, MACD, BOLL, RSI, KDJ, Stoch RSI\}$$
 (1)

In the following, calculate the spearman correlation coefficient [5].

The Spearman correlation coefficient is applied to data that do not satisfy a linear relationship and do not satisfy a normal distribution, in accordance with the index selected in this case.

When calculated with Spearman's correlation coefficient,

As shown in the table below, none of our six selected indicators correlate between the decision outcomes generated by gold and bitcoin. It passes the correlation test and we can use it for fuzzy evaluation. Spearman's correlation coefficient table for gold is shown as table 1. Spearman's correlation coefficient table for bitcoin is shown as table 2.

Table 1: Spearman's correlation coefficient table for gold

		V1	V2	V3	V4	V5	V6
Spearman Rho	V1	r 1.000	.244**	.027	007	.002	067**
	V2	r .244**	1.000	.000	.011	.004	169**
	V3	r .027	.000	1.000	.105**	055*	010
	V4	r007	.011	.105**	1.000	073**	542**
	V5	r .002	.004	055*	073**	1.000	005
	V6	r067**	169**	010	542**	005	1.000

<sup>\*\*.</sup> At the 0.01 level, the correlation is significant.

Table 2: Spearman's correlation coefficient table for bitcoin

-		V1	V2	V3	V4	V5	V6
Spearman Rho	V1	r 1.000	.160**	.076**	.006	.000	062**
	V2	r .160**	1.000	$.092^{**}$	.000	.000	154**
	V3	r .076**	.092**	1.000	.030	048*	075**
	V4	r .006	.000	.030	1.000	$.062^{**}$	477**
	V5	r .000	.000	048*	.062**	1.000	001
	V6	r062**	154**	075**	477**	001	1.000

<sup>\*\*.</sup> At the 0.01 level, the correlation was significant.

#### (2) Establishment of the rubric set

The set of comments is calculated as follows [2]:

$$Y = \{f_i(x)\}\tag{3}$$

Among them,  $f_i(x)$  is the rubric function corresponding to the i-th factor,  $1 \le i \le 6$ .

$$f_1(x) = \begin{cases} 1, & \text{when the short term averages} \\ & \text{crosses the long term averages upwards} \\ 0, & \text{when short term averages and} \\ & \text{long term averages do not cross} \\ -1, & \text{when the short term average crosses down} \\ & \text{through the long term average} \end{cases}$$

$$(4)$$

Here, we use 5 and 10 days as short and long term respectively.

$$f_2(x) = \begin{cases} 1, & \text{when MACD turns from negative to positive} \\ 0, & \text{when the sign of MACD does not change} \\ -1, & \text{when MACD turns from positive to negative} \end{cases}$$
 (5)

$$f_3(x) = \begin{cases} 1, & \text{when the daily price crosses DN or moves up through MB} \\ 0, & \text{other} \\ -1, & \text{when the daily price crosses UP or down through MB} \end{cases}$$
 (6)

Among them, MD is the standard deviation, MB is mid-track line, UP is upper track line, DN is low track line.

<sup>\*.</sup> At the 0.05 level, the correlation is significant.

<sup>\*.</sup> At the 0.05 level, the correlation was significant.

$$f_4(x) = \begin{cases} 4, when RSI \in [80,100] \\ 3, when RSI \in [50,80) \\ 2, when RSI \in [20,50) \\ 1, when RSI \in [0,20) \\ 0, when RSI = 0 \end{cases}$$
 (7)

$$f_{5}(x) = \begin{cases} 1, when \ D > 20, K > D, J < 0 \ and \ the \ x \ of \ intersections \\ \in [-\infty, 20] \cup [80, +\infty] \\ 0, other \\ -1, when \ D > 80, K < D, J > 100 \ and \ the \ x \ of \ intersections \\ \in [-\infty, 20] \cup [80, +\infty] \end{cases}$$
(8)

Among them, line K is a fast confirmation line. Line D is the slow trunk line. Line J is a direction sensitive line.

$$f_6(x) = \begin{cases} 1, when SRSI \le 0.2\\ 0, when 0.2 < SRSI < 0.8\\ -1, when SRSI \ge 0.8 \end{cases}$$
 (9)

Calculating the above formula, we get the decision made according to the indicator.

Here is an example of quantitative analysis of trading intentions for gold. At day 77, the analysis is performed on each indicator to find its factor results as table3.

Table 3: The score of each indicator at day 77

gold	MA	MACD	BOLL	RSI	KDJ	Stoch RSI
score	-1	0	-1	3	1	0

The relationship  $\tilde{R}$  between X and Y is then represented by the fuzzy matrix as:

$$\tilde{R} = (-1, 0, -1, 3, 10)^T$$
 (10)

Among them,  $\tilde{R}$  is single factor evaluation matrix. We use a single-factor evaluation method to perform the evaluation of transaction intentions based on a single-factor evaluation matrix. The specific principles are as table4:

Table 4: Exponential scale

scale	meaning
1	equally important
3	A is slightly more important than B
5	A is significantly more important than B
7	A is more strongly important than B
9	A is more important than B in the extreme
2,4,6,8	assign importance according to the size of the number

Based on the above table, the constructing matrix is as table5.

Table 5: The constructing matrix of indicator

	MA	MACD	BOLL	RSI	KDJ	Stoch RSI
MA	1	1/2	3	4	2	4
MACD	2	1	4	5	3	5
BOLL	1/3	1/4	1	2	1/2	2
RSI	1/4	1/5	1/2	1	1/3	1
KDJ	1/2	1/3	2	3	1	3
Stoch RSI	1/4	1/5	1/2	1	1/3	1

This is a positive reciprocal matrix of order six, and the corresponding normalized eigenvectors are obtained using MATLAB as follows:

$$\tilde{A} = (0.2484 \ 0.3814 \ 0.0966 \ 0.0585 \ 0.1566 \ 0.0585)$$
 (11)

So, we got:

$$\begin{cases}
CI = 0.0162 \\
RI = 1.2462 \\
CR = \frac{CI}{RI} = 0.0130
\end{cases}$$
(12)

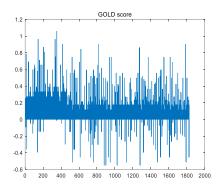
The above passes the consistency test, so  $\omega$  can be used as the weight vector.

Obviously  $\tilde{A}$  is a fuzzy set on the theoretical domain X, we use fuzzy transformation to obtain.

$$\tilde{B} = \tilde{A} * \tilde{R} \tag{13}$$

Analyzing the fuzzy set we get and then calculate the results. We got the daily trading intention score.

The fuzzy set obtained from the analysis is analyzed and the results are calculated. We obtain daily trading intention scores for gold and bitcoin.



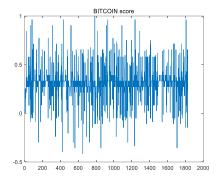


Figure 1: Rating of decisions made on gold

Figure 2: Rating of decisions made on bitcoin

# 2.2. Building the investment multivariate quantitative model

When investing in products, the classical mean-variance model uses only a single technical index to measure the variability of products. This analysis method with single technical index often has limitations and is particularly prone to giving incorrect buy and sell signals[4].

Based on the above, for a product, we calculated its six indicators including MA and MACD, and combined multiple technical index analysis methods through fuzzy comprehensive evaluation to form two trade recommendation values for gold and bitcoin. The value of this recommendation is dimensionless and reflects only the degree of recommendation for buying and selling. The more the value deviates from the 0 value line, the stronger the recommendation for buying or selling, which reflects the product price and market operation from several angles.

Therefore, when allocating investment ratio, we first set an initial ratio  $(W_{x_0}, W_{g_0}, W_{b_0})$  for cash, gold, and bitcoin, and use the above trade recommendation values to calculate our ideal ratio for the next trading day. The calculation formula is as follows. Let the trading day be the i-th day. Let the trade recommendation values of gold and bitcoin trading on the trading day be  $S_{g_i}, S_{b_i}$ .

$$W_{g_i} = \frac{W_{g_{(i-1)}} + kS_{g_i}}{\left(W_{g_{(i-1)}} + kS_{g_i}\right) + \left(W_{b_{(i-1)}} + kS_{b_i}\right) + W_x}$$
(14)

$$W_{b_i} = \frac{W_{b_{(i-1)}} + kS_{b_i}}{\left(W_{g_{(i-1)}} + kS_{g_i}\right) + \left(W_{b_{(i-1)}} + kS_{b_i}\right) + W_x} \tag{15}$$

$$W_{x_i} = 1 - W_{a_i} - W_{b_i} (16)$$

Among them, the k in the formula is the risk tolerance factor, which is the magnitude of adjustment and can be adjusted by the investor, meaning the percentage of risky assets that the investor can accept. The value of k is larger when the proportion of acceptable risky assets is larger. When the risk tolerance k became larger, the proportion of risky assets increased and therefore the adjustment to various types of resources became larger, and it ccelerated changes in the share of corresponding product inputs. In this case, each asset can be quickly adjusted to the desired ratio, but this can also lead to higher investment risk and increased fees due to significant redeployment. Therefore, this factor needs to be set by the

investor on the basis of his ability. Here, we recommend a factor of 0.24 for the following reasons. Based on the above ratio determination method, we obtained the recommended adjustment ratio  $(W_{x_i}, W_{g_i}, W_{b_i})$  for each asset for the next trading day. Take the trading process of k=0.01 and k=0.1 as examples, the corresponding changed in each asset are shown in the chart above.

Next, based on the determined recommended percentage of each asset for the next trading day, we can then modified it by incurring transactions.

Let the total value of the assets at that date be  $sum_i$ , the target market value of each asset before the opening of the next trading day is  $(Q_{x_i}Q_{g_i}Q_{b_i})$ , the change in market value between the first and second days is  $\Delta$ . Let transaction fee of the one-time adjustment be C, the commission rates for gold and bitcoin are  $r_g$ ,  $r_g$ .

The calculation formula are as follows:

$$sum_i = Q_{x_i} + Q_{g_i} + Q_{b_i} \tag{17}$$

$$\begin{cases} Q_{x_i} = sum_i * W_{x_i} \\ Q_{g_i} = sum_i * W_{g_i} \\ Q_{b_i} = sum_i * W_{b_i} \end{cases}$$

$$(18)$$

$$\begin{cases}
\triangle_{x} = Q_{x_{i}} - Q_{x_{(i-1)}} \\
\triangle_{g} = Q_{g_{i}} - Q_{g_{(i-1)}} \\
\triangle_{b} = Q_{b_{i}} - Q_{b_{(i-1)}}
\end{cases}$$
(19)

$$\begin{cases}
C_g = r_g * \triangle_g \\
C_b = r_b * \triangle_b
\end{cases}$$
(20)

Let the fee for that day be  $C_i$  and the fee generated by a single recursive fine-tuning be c. Then this formula is:

$$C_i = \sum c \tag{21}$$

From this, the model enables the deployment of assets, calculates the fees generated by the deployment and the market value of the assets held after the deployment. For example, using the risk tolerance factor k=0.1, the curve of the change in the market value of our asset holdings is shown as figure 3. Corresponding daily commissions is shown as figure 4.

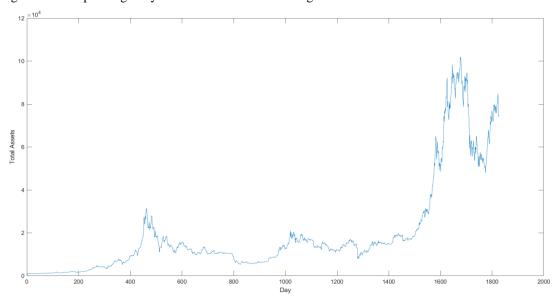


Figure 3: Total asset curve at k = 0.1

Since setting different risk tolerance factors can have a significant impact on the overall investment process, we used this investment as the subject of our study, to explore the change in final assets of investment users when setting different risk tolerance factors. We were committed to finding the most appropriate risk tolerance factor that will maximize the investor's return when using this factor. This

value will be used as a guideline for solving other similar problems using this model in the future. The results of the solution are as follows: On the interval  $k \in (0,1)$ , the variation of investment return with the value of k is shown in figure 5. When  $k \in (0,1)$  (universally applicable), the change in investment return with k is shown as follows.

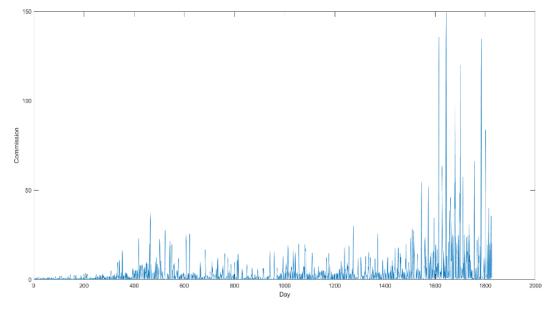


Figure 4 Corresponding daily commissions

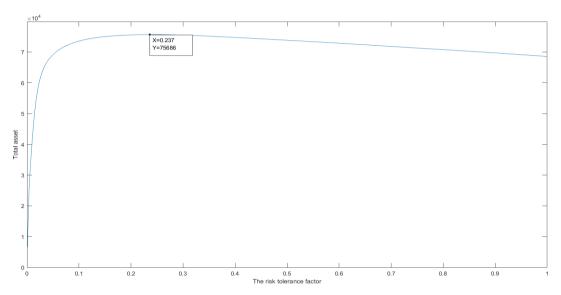


Figure 5: The change in investment return with k

From the figure 5, it can be seen that the user investment returns tends to increase and then decrease with the increase of k and reaches the maximum at k=0.237. At that point, the user's assets are 7.5686e+04.

Therefore, we can obtain 0.237 as the optimal risk tolerance factor for the investment situation of this topic. We used this as a guideline for this model, so that it can be used as a reference by other users.

In summary, we use the above established investment multivariate quantitative technical analysis model for portfolio analysis. With the selection of a suitable risk tolerance index, we reasonably conjecture that the initial \$1000 investment worth \$7.5686e+04 on 9/10/2021.

#### 2.3. Daily decision

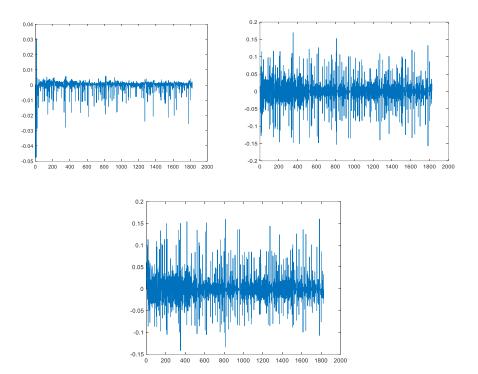


Figure 6: Daily rate adjustment decisions for cash, gold, bitcoin

As shown in the figure6, the three charts above together make up the daily adjustment decision. When the value of an asset type decision is a positive value, it means that a decision was made on that day to increase the ratio of that asset on the next trading day, and conversely, a decision was made to decrease the ratio of that asset on the next trading day.

# 3. Present evidence that your model provides the best strategy

# 3.1. Transaction success rate

We call a trade a success when we make a profit or avoid a loss today from a trade we made yesterday.

As an example, the trading success rate of gold is calculated as follows:

(1) Synthesize trade recommendation values to get trading decisions

When we decide to buy, that is, to predict that its price will increase, it is recorded as 1, and to sell (predicting that the price will decrease) as -1. If no trade is made (predicting that the price will remain unchanged) it is recorded as 0.

The formula is as follow:

$$d_g(i) = \begin{cases} 1, S_{g_i} > 0 \\ 0, S_{g_i} = 0 \\ -1, S_{g_i} < 0 \end{cases}$$
 (22)

(2) Calculate the actual change in the price of gold

When the price of gold actually rises, it is recorded as 1, when it falls, it is recorded as -1, and when it remains unchanged, it is recorded as 0.

Let  $V_a(i)$  be the gold price on day I. The formula is as follow:

$$d_1(i) = \begin{cases} 1, V_g(i) > V_g(i-1) \\ 0, V_g(i) = V_g(i-1) \\ -1, V_g(i) < V_g(i-1) \end{cases}$$
 (23)

# (3) Calculate the matching rate

That is, the success rate of the transaction. The formula is as follow:

$$\begin{cases} f(x) = \frac{\sum_{x=1}^{1825} g(x)}{1825} \\ g(x) = \begin{cases} 1, d_g(i) = d_1(i) \\ 0, d_g(i) \neq d_1(i) \end{cases} \end{cases}$$
(24)

1000 1200 1400 1600 1800 2000

The final success rate for gold is 70.86%. Similarly, we can find 60.04% for bitcoin. It can be considered that the prediction results are informative and the model works well.

# 3.2. The trend of proportional change is reasonable

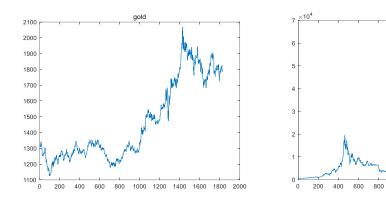


Figure 7: The change trend of gold price and bitcion price

The change trend of gold price and bitcion price is shown as figure6, bitcoin has risen tremendously compared to gold, which means that the returns from investing in bitcoin are much greater than gold. Common sense dictates that we should invest more in the direction of bitcoin when making investment decisions.

# 3.3. Consider risk-taking factor

In the quantitative technical analysis model of investment multivariate used in this case, we introduced a risk-taking factor. It is expressed in the calculation formula as the magnitude of the amplification for each adjustment, i.e. the investor's risk tolerance.

Because of the setting of this coefficient, we can generate different investment ratios for users with different investment backgrounds in order to meet the needs of different investors:

- (1) Richer investors may increase the value of this factor, meaning that they can accept a larger capital deficit. This is riskier, but may also yield more benefits. As shown in the chart below, when the k value is set to 2, a single high yielding match is generated with a gaining asset of \$115,000.
- (2) Investors with average economic status can reduce the value of this coefficient, making our portfolio generate more robust returns.

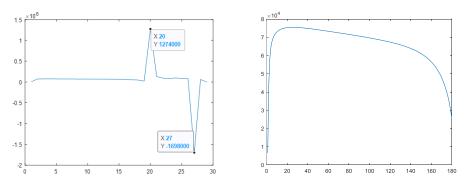


Figure 8: Risk tolerance-return graph

In the solution of 4.1.2, we limit the risk-taking coefficient to a risk range that is generally acceptable, i.e., k is set between 0,1, and the maximum return in this range is \$7.5686e+04, which corresponds to a value of 0.237, which is more in line with the investment needs of the general public. In this respect, the model is applicable to a wide range of people and can be used flexibly.

As can be seen from the figure 8 below, the returns mostly remain positive regardless of the k-value setting i.e. the model is guaranteed to produce returns in most cases and the model works better.

In summary, it can be demonstrated that the investment multivariate quantitative technical analysis model we use is the best strategy.

#### 4. Conclusion

In solving the proposed value of gold and bitcoin trading, we selected six indicators with low correlation and used a fuzzy evaluation model for comprehensive consideration, reflecting the product price and market operation from multiple perspectives, avoiding the limitations of a single indicator. Then, e choose to invest by constantly adjusting the allocation of each asset class. Starting from the change of assets and calculating commissions by the amount of change of assets avoids the tedious process arising from each trade entry. The model introduces a risk tolerance coefficient, which can provide traders with different investment ratios for different investment backgrounds to meet the needs of different investors and make the decision model more flexible. We also find the guideline value 0.237 to provide traders with reasonable suggestions for their investment choices.

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