Application of QUBO model in credit score card combination optimization

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Abstract. Credit cards are a rule by which banks rate their customers. Different credit scoring cards have different thresholds, corresponding to different pass rates and bad debt rates, which have a crucial impact on the bank's revenue. To help banks choose the best combination of credit scoring cards, so as to maximize revenue. Based on the triple credit card combination strategy of the bank, this paper establishes a mathematical programming model for solving the optimal combination. Aiming at the particularity of the binary decision variables, a constraint method is proposed to transform the quartic and quartic terms in the model into quadratic terms. Then, in order to balance the relationship between the objective function and the constraint conditions, the weighted penalty coefficient is further introduced by combining the entropy weight method. The model is transformed into QUBO(quadratic unconstrained binary optimization) model, and then combined with the bank's credit score card data, the optimal combination is solved by quantum annealing algorithm and verified by experiment. The experimental results show that this method has high precision and strong applicability in solving combinatorial optimization problems.

Keywords: entropy weight method, Penalty coefficient, QUBO, quantum annealing.

1. Introduction

In the business of bank credit card or related loan, it is necessary to use credit score card to evaluate the credit rating of the customer before granting credit to the customer, and multiple combination rules are often used to score the customer[1-3].However, different credit score cards have different thresholds, which makes different credit score cards correspond to different pass rates and bad debt rates under different thresholds. For banks, the higher the approval rate, the more customers will pass the loan qualification examination, and the more interest input the bank will get. However, the higher the approval rate generally corresponds to the high bad debt rate, and the higher the bad debt rate means the greater the risk of capital loss. Therefore, choosing a reasonable credit score card combination and its threshold has a crucial impact on the bank's profits.

The banking scenario is very complex and often requires the combination of several different credit scoring cards to achieve the best risk control strategy. Selecting the best credit score card to maximize the bank's profit is obviously a combinatorial optimization problem. Combinatorial optimization problems usually belong to NP-hard problems with large-scale search space and no known polynomial-time algorithm can solve the optimal solution. The traditional solution method is to use heuristic algorithm or approximation algorithm to approximate the optimal solution. The solution speed is slow and it is easy to fall into the local optimal solution.

For this kind of combinational optimization problem, it can be converted into QUBO model [4-8] and calculated with quantum annealing algorithm, which can take advantage of the parallelism of quantum computing to accelerate the solution process, and effectively avoid falling into the local optimal solution by controlling the coupling strength of qubits [9-12]. Therefore, this paper uses the entropy weight method to build a weighted Penalt coefficient to balance the relationship between constraints and objective functions [13,14], and establishes a QUBO model for the bank's multiple credit score card combination problem, and then uses the quantum annealing algorithm to solve it, providing an effective solution for the bank's multiple credit score card combination optimization problem.

2. Establishment of QUBO model for credit score card combination optimization

2.1. Credit score card combination strategy

According to the survey, the three credit score cards of a certain bank have 10 thresholds respectively, and each threshold corresponds to different pass rate and bad debt rate. Specific data are shown in Table 1:

Table 1. Three credit scoring cards of a bank

Credit score Card 1			Credit score Card 2			Credit score Card 3		
threshold value	passing rate	bad debt rate	threshold value	passing rate	bad debt rate	threshold value	passing rate	bad debt rate
1	76.00%	1.30%	1	72.00%	3.20%	1	80.00%	1.20%
2	77.00%	1.50%	2	73.00%	3.80%	2	82.00%	1.30%
3	78.00%	1.70%	3	76.00%	5.00%	3	83.00%	2.40%
4	80.00%	2.40%	4	77.00%	5.30%	4	86.00%	4.00%
5	82.00%	2.60%	5	79.00%	6.50%	5	89.00%	4.20%
6	84.00%	2.80%	6	82.00%	7.40%	6	92.00%	5.70%
7	87.00%	3.00%	7	86.00%	7.60%	7	93.00%	6.80%
8	93.00%	3.60%	8	87.00%	7.90%	8	94.00%	6.90%
9	94.00%	4.30%	9	91.00%	8.00%	9	97.00%	7.00%
10	96.00%	5.20%	10	92.00%	8.40%	10	98.00%	7.30%

The bank chooses a triple credit score card strategy. If the total pass rate of the three credit score cards is t and the total bad debt rate is m, then:

$$\begin{gathered} t = p_1 p_2 p_3 \\ m = \frac{1}{3}(h_1 + h_2 + h_3) \end{gathered} \tag{1}$$

Where, $p_1(p_2, p_3)$ and $h_1(h_2, h_3)$ represent the pass rate and bad debt rate of the first (second, third) credit score card respectively. If the loan fund is w and the interest income rate is η, the final income of the bank is expressed as:

$$r = w\eta p_1 p_2 p_3 \left[1 - \frac{1}{3}(h_1 + h_2 + h_3)\right] - w p_1 p_2 p_3 \left[\frac{1}{3}(h_1 + h_2 + h_3)\right] \tag{2}$$

Therefore, choosing a different combination of thresholds among the three credit scoring cards can affect a bank's final revenue.

2.2. Establish a general form of planning model

First, a general programming model is established, and three binary variables are set to indicate whether the first card, the second card and the third card under the i threshold are selected. According to the method of calculating bank income in formula (1) and (2), the planning model is established with the maximum income as the objective function and each credit score card can only select one threshold as the constraint condition.

(1) Decision variables:

According to the combination strategy of the bank's triple credit score card, three binary decision variables are set as follows:

$$x_{i1}=\begin{cases}1, & select\ the\ first\ card\ under\ the\ i\ threshold\\ 0, & the\ first\ card\ under\ the\ i\ threshold\ is\ not\ selected\end{cases}$$
$$x_{j2}=\begin{cases}1, & select\ the\ second\ card\ under\ the\ j\ threshold\\ 0, & the\ second\ card\ under\ the\ j\ threshold\ is\ not\ selected\end{cases} \tag{3}$$
$$x_{k3}=\begin{cases}1, & select\ the\ third\ card\ under\ the\ k\ threshold\\ 0, & the\ third\ card\ under\ the\ k\ threshold\ is\ not\ selected\end{cases}$$

Where $i,j,k=1,2,...,10$.

(2) Objective function:

According to the triple credit score card combination strategy, combined with formula (1) and (2), the total pass rate after the combination of three credit score cards is set as follows:

$$t_{ijk}=p_{i1}x_{i1}p_{j2}x_{j2}p_{k3}x_{k3} \tag{4}$$

The total bad debt ratio after the combination of the three credit scoring cards is:

$$m_{ijk}=\frac{1}{3}(h_{i1}x_{i1}+h_{j2}x_{j2}+h_{k3}x_{k3}) \tag{5}$$

Where $p_{i1}(p_{j2},\ p_{k3})$ represents the pass rate of the $i(k,l)$ threshold when the first (second,third) card is selected, and h represents the bad debt rate of the $i(k,l)$ threshold when the first (second,third) card is selected.

Based on this, the objective function is defined as:

$$\begin{aligned}\max\ z=\sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{j=1}^{10} w\eta p_{i1}x_{i1}p_{j2}x_{j2}p_{k3}x_{k3}\left[1-\frac{1}{3}(h_{i1}x_{i1}+h_{j2}x_{j2}+h_{k3}x_{k3})\right]\\ -wp_{i1}x_{i1}p_{j2}x_{j2}p_{k3}x_{k3}\left[\frac{1}{3}(h_{i1}x_{i1}+h_{j2}x_{j2}+h_{k3}x_{k3})\right]\end{aligned} \tag{6}$$

(3) Constraints:

Since each credit score card can only select one threshold, it needs to meet the following equation constraints:

$$\sum_{i=1}^{10}x_{i1}=1,\ \sum_{j=1}^{10}x_{j2}=1,\ \sum_{k=1}^{10}x_{k3}=1 \tag{7}$$

In summary, a goal planning model specifying the selection thresholds of three credit score cards is established as follows:

$$\max\ z=\sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{j=1}^{10}w\eta p_{i1}x_{i1}p_{j2}x_{j2}p_{k3}x_{k3}\left[1-\frac{1}{3}(h_{i1}x_{i1}+h_{j2}x_{j2}+h_{k3}x_{k3})\right]$$
$$-wp_{i1}x_{i1}p_{j2}x_{j2}p_{k3}x_{k3}\left[\frac{1}{3}(h_{i1}x_{i1}+h_{j2}x_{j2}+h_{k3}x_{k3})\right]$$
$$s.t.\begin{cases}\sum_{i=1}^{10}x_{i1}=1\\ \sum_{j=1}^{10}x_{j2}=1\\ \sum_{k=1}^{10}x_{k3}=1\\ x_{i1},x_{j2},x_{k3}=0\ or\ 1\\ i,j,k=1,2,...,10.\end{cases} \tag{8}$$

2.3. Transformation of the QUBO model

Cubic and quartic terms appear in the general form programming model, which undoubtedly brings great difficulties to the solution. In order to simplify the calculation and speed up the solution, this paper first transforms the cubic and quartic terms into quadratic terms by using constraints, and then transforms the general form programming model into QUBO model, which is solved by quantum annealing algorithm.

The x formula is further organized and simplified as follows:

$$\max\ z=\sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{k=1}^{10}w\eta p_{i1}p_{j2}p_{k3}x_{i1}x_{j2}x_{k3}-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{i1}x^{2}{}_{i1}x_{j2}x_{k3}(\eta-1)$$
$$-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{j2}x_{i1}x^{2}{}_{j2}x_{k3}(\eta-1)-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{k3}x_{i1}x_{j2}x^{2}{}_{k3}(\eta-1) \tag{9}$$

Let $y_{i1}=x_{i1}x_{j2}$, $y_{j2}=x_{i1}x_{k3}$, $y_{k3}=x_{j2}x_{k3}$, Plug in formula (7)

$$\max\ z=\sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{k=1}^{10}w\eta p_{i1}p_{j2}p_{k3}y_{i1}x_{k3}-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{i1}y_{i1}y_{j2}(\eta-1)$$
$$-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{j2}y_{i1}y_{k3}(\eta-1)-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{k3}y_{j2}y_{k3}(\eta-1) \tag{10}$$

After replacing with y_{i1},y_{j2},y_{k3},the following equality constraints must be met:

$$\begin{cases}y_{i1}-x_{i1}x_{j2}=0\\ y_{j2}-x_{i1}x_{k3}=0\\ y_{k3}-x_{j2}x_{k3}=0\end{cases} \tag{11}$$

To deal with the constraints of the first $y_{i1}-x_{i1}x_{j2}=0$ as an example, set the function $H_1=y_{i1}-x_{i1}x_{j2}$, then the quadratic polynomial constraints formed by x_{i1}, x_{j2}, y_{i1} can be expressed as:

$$H_1{}'=\beta_1x_{i1}+\beta_2x_{j2}+\beta_3y_{i1}+\beta_4x_{i1}x_{j2}+\beta_5x_{i1}y_{i1}+\beta_6x_{j2}y_{i1} \tag{12}$$

In order to maximize the final income of the bank, when the coefficients meet the equation (10), it is stipulated. Since the variable is a binary variable, it has the following properties:

When $y_{i1}=1$, $x_{i1}=1, x_{j2}=1$, satisfy $H_1{}'=0$;

For $y_{i1}=0$, $x_{i1}=0, x_{j2}=1\ or\ x_{i1}=1, x_{j2}=0$, satisfies $H_1{}'=0$.

Therefore, the coefficients are determined by derivation as follows:

$(\beta_1,\ \beta_2,\ \beta_3,\ \beta_4,\ \beta_5,\ \beta_6)=(0,0,3,1,-2,-2)$, then $H_1{}'$ is represented by

$$H'_1=3y_{i1}+x_{i1}x_{j2}-2x_{i1}y_{i1}-2x_{j2}y_{i1} \tag{13}$$

Similarly, the same treatment can be done for other equality constraints. Set $H_2=y_{k2}-x_{i1}x_{l3}$ and $H_3=y_{k3}-x_{j2}x_{k3}$, then the above equation constraints can be converted into:

$$\begin{cases} 3y_{i1}+x_{i1}x_{j2}-2x_{i1}y_{i1}-2x_{j2}y_{i1}=0 \\ 3y_{j2}+x_{i1}x_{k3}-2x_{i1}y_{j2}-2x_{k3}y_{j2}=0 \\ 3y_{k3}+x_{j2}x_{k3}-2x_{j2}y_{k3}-2x_{k3}y_{k3}=0 \end{cases} \tag{14}$$

In order to maximize the objective function, the weighted Penalty coefficient P is introduced, which should satisfy $P>0$. Since all QUBO models are quadratic terms, so $y_{i1}^2=y_{i1}\,(y_{j2}^2=y_{j2}, y_{k3}^2=y_{k3})$, then the weighted Penalty coefficient is used to add the constraint term to the objective function to transform the QUBO model of quadratic unconstrained binary optimization into:

$$\begin{aligned} \max\ z=\sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{k=1}^{10} & w\eta p_{i1}p_{j2}p_{k3}y_{i1}x_{k3}-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{i1}y_{i1}y_{j2}(\eta-1) \\ & -\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{j2}y_{i1}y_{k3}(\eta-1)-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{k3}y_{j2}y_{k3}(\eta-1) \\ & -P(3y_{i1}^2+x_{i1}x_{j2}-2x_{i1}y_{i1}-2x_{j2}y_{i1}) \\ & -P(3y_{j2}^2+x_{i1}x_{k3}-2x_{i1}y_{j2}-2x_{k3}y_{j2}) \\ & -P(3y_{k3}^2+x_{j2}x_{k3}-2x_{j2}y_{k3}-2x_{k3}y_{k3}) \end{aligned} \tag{15}$$

Then, it is necessary to consider adding the constraint that each credit score card can only select one threshold to the objective function. In order to make it more reasonable, this paper introduces the weighted Penalty coefficient, set the weighted Penalty coefficient as $weight_\lambda P, (\lambda=1,2,3)$, where $P>0$, then the final QUBO model is as follows:

$$\max\ z=\sum_{i=1}^{10}\sum_{j=1}^{10}\sum_{k=1}^{10} w\eta p_{i1}p_{j2}p_{k3}y_{i1}x_{k3}-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{i1}y_{i1}y_{j2}(\eta-1)$$
$$-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{j2}y_{i1}y_{k3}(\eta-1)-\frac{1}{3}wp_{i1}p_{j2}p_{k3}h_{k3}y_{j2}y_{k3}(\eta-1)$$
$$P\left[weight_1\left(\sum_{i=1}^{10}x_{i1}-1\right)^2-weight_2\left(\sum_{j=1}^{10}x_{j2}-1\right)^2-weight_3\left(\sum_{k=1}^{10}x_{k3}-1\right)^2\right] \tag{16}$$
$$-P(3y_{i1}^2+x_{i1}x_{j2}-2x_{i1}y_{i1}-2x_{j2}y_{i1})$$
$$-P(3y_{j2}^2+x_{i1}x_{k3}-2x_{i1}y_{j2}-2x_{k3}y_{j2})$$
$$-P(3y_{k3}^2+x_{j2}x_{k3}-2x_{j2}y_{k3}-2x_{k3}y_{k3})$$

Further, by setting a reasonable Penalty coefficient, a specific additive constant C and matrix Q can be obtained, so that the form of the model is transformed into:

$$\max\ z=x^TQ\,x+C \tag{17}$$

It is equivalent to finding the optimal solution of the following model:

$$\max\ z=x^TQ\,x \tag{18}$$

Where x is the row vector, $x=(x_{i1}{}^T,x_{k2}{}^T,x_{l3}{}^T,y_{i1}{}^T,y_{k2}{}^T,y_{l3}{}^T)$.

2.4. The weight of weighted Penalty coefficient is determined

When an objective function has multiple constraints, it is necessary to consider the importance of each constraint condition as a whole, so that it is more reasonable to uniformly transform multiple constraints into an unconstrained optimization problem. According to the data of credit scoring card 1, card 2 and card 3 in Table 1, the entropy weight method is used to calculate the pass rate weight and bad debt rate weight of the three cards under different thresholds, and then the comprehensive weight is further obtained, which is used as the weight of each constraint condition.

Take the calculation of the pass rate weight as an example, the specific steps are as follows:

Step 1: The pass rate data of the three credit score cards are sorted into matrix $D=(d_{ij})_{10\times3}$, then the proportion of the j credit score card under the i threshold is:

$$p_{ij}=\frac{d_{ij}}{\sum_{i=1}^{10}d_{ij}} \tag{19}$$

Where, $i=1,2,\cdots,10$； $j=1,2,3$

Step 2: Calculate the entropy of the first credit score card:

$$e_j=-\frac{1}{\ln 10}\sum_{i=1}^{10}p_{ij}\ln p_{ij} \tag{20}$$

Step 3: Calculate the coefficient of variation of the first credit score card:

$$z_j = 1 - e_j \tag{21}$$

For j credit score cards, the larger the z_j, the smaller the corresponding degree of variation, and the smaller the z_j, the greater the corresponding degree of variation.

Step 4: Calculate the weight of the first credit score card:

$$wt_j = \frac{z_j}{\sum_{j=1}^{3} z_j} \tag{22}$$

According to the above method, the pass rate weights of three credit scoring cards can be calculated.

When solving the weight of bad debt rate, we should first carry out positive processing, transform the cost-oriented indicator into the benefit indicator, organize the bad debt rate data of three credit scoring cards into matrix $M = (n_{ij})_{10\times 3}$, which can be converted by the following methods:

$$\tilde{n}_{ij} = 1 - \frac{n_{ij}}{\max_j (n_{ij})} \tag{23}$$

Then, the weight of bad debt rate of the three credit scoring cards is solved according to the above method, and the weight of bad debt rate is set as, then the comprehensive weight is defined as:

$$weight_j = \frac{wt_j + wh_j}{2} \tag{24}$$

Based on this, the comprehensive weight is defined as the weight of weighted Penalty coefficient.

3. Results

3.1. 3.1 The solution of the QUBO mode

In this paper, quantum annealing algorithm is used to solve the QUBO model, which can take advantage of the parallelism of quantum computing to process multiple possible solutions at the same time, thus speeding up the solution speed. And compared with the traditional classical annealing algorithm, quantum annealing algorithm uses quantum random walk to explore the solution space, which can avoid falling into the local optimal solution through the coupling strength of qubits.

As shown in Table 2, according to the steps of the entropy weight method, the pass rate weight, bad debt rate weight and comprehensive weight of the three cards can be solved as follows:

Table 2. Weight of credit score card constraints

weight	Credit score card 1	Credit score card 2	Credit score card 3
Pass rate	0.3706	0.3802	0.2492
Bad debt ratio	0.1743	0.3900	0.4357
Comprehensive	0.2725	0.3851	0.3425

The comprehensive weight is the average weight of the pass rate weight and the bad debt rate weight. The comprehensive weight of the credit score card is arranged as card 2, card 3, and card 1, which are 0.3851, 0.3425, and 0.2725 respectively.

Further, the Penalty coefficient is set to 100000, and the quantum annealing algorithm is adopted to solve the problem. The loan fund of 1000000 yuan and the interest income rate of 8% of the bank are inserted into the model, and the credit score card combination is solved as shown in Table 3:

Table 3. Optimal combination of credit score card thresholds

Credit score card	1	2	3
Threshold value	8	1	2
Through rate	93%	72%	82%
Bad debt ratio	3.6%	3.2%	1.3%

It is concluded that when the thresholds of credit score card 1, 2 and 3 are 8, 1 and 2 respectively, the bank's income is the largest, which is 27914.82 yuan.

3.2. Analysis of experimental results

Calculate the bank income of all the credit score card threshold combinations and make a visual image in Figure 1.

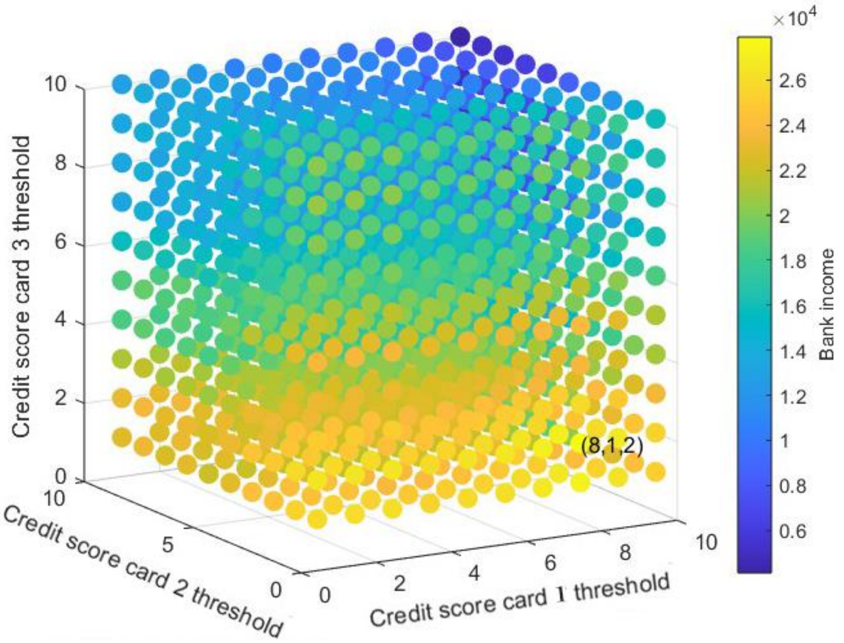

Figure 1. Bank income under different combinations

As can be seen from Figure 1, when the bank income is high, the threshold of credit card 3 is mainly required to be as low as possible. The yellow area indicates that the bank income is above 20,000 yuan, and the final bank income solved by the quantum annealing algorithm is 27914.82 yuan, which is consistent with the actual situation and has a good effect of searching for the optimal solution.

4. Conclusion

It is an NP-hard combinatorial optimization problem to help banks choose triple credit score card combinations for maximum benefit. Although there are many combinatorial optimization problems using QUBO model, the problem studied in this paper is not one of them. The reason is that the calculation of bank income in the problem involves the joint action of the pass rate and bad debt rate of the three credit scoring cards, and the model produces the fourth term and the third term, and contains multiple constraints. In fact, these problems are difficult for QUBO model to solve, and the constraint method proposed in this paper effectively converts quartic and cubic terms into quadratic terms, and objectively introduces the weighted Prently coefficient by using the entropy weight method to balance the relationship between the objective function and the constraint conditions. In terms of the solution method, the quantum annealing algorithm is used for experimental verification. Different from other traditional intelligent optimization algorithms, it has a high degree of parallelism, and can handle more computing tasks in the same time, and the optimization speed is fast. Experiments show that the results obtained by the algorithm are consistent with the actual values, which indicates that the application of QUBO model to credit card combination optimization in this paper is successful, and provides theoretical guidance for banks to make use of multiple credit card combinations to obtain the maximum profit.

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