

### 介绍



本教程基于 IBM 的 Qiskit, Qiskit[finance] 编写。

#### 本教程包含:

1. 分散投资数学模型

2. 量子算法 - 通过VQE求解问题

3. 代码实例

\* TODO: 完善算法的详细解读

#### Qiskit:

https://qiskit.org/documentation/getting\_started.html Oiskit finance:

https://qiskit.org/documentation/finance/tutorials/index.html

#### Github & Gitee 代码地址:

https://github.com/mymagicpower/qubits/tree/main/quantum\_qiskit\_finance/02\_portfolio\_diversification.py https://gitee.com/mymagicpower/qubits/tree/main/quantum\_qiskit\_finance/02\_portfolio\_diversification.py





#### 虚拟环境

# 创建虚拟环境
conda create -n ENV\_NAME python=3.8.0
# 切换虚拟环境
conda activate ENV\_NAME
# 退出虚拟环境
conda deactivate ENV\_NAME
# 查看现有虚拟环境
conda env list
# 删除现有虚拟环境
conda remove -n ENV\_NAME --all

#### 安装 Qiskit

#### pip install qiskit

# install extra visualization support
# For zsh user (newer versions of macOS)
# pip install 'qiskit[visualization]'

pip install qiskit[visualization]

#### 安装 Qiskit[finance]

# For zsh user (newer versions of macOS)
# pip install 'qiskit[finance]'

pip install qiskit[finance]

# 分散投资数学模型



数学模型将资产根据相似度聚簇,每个簇选择一个代表作为指数基金投资组合一部分。

 $\rho_{ij} = \text{similarity between stock } i \text{ and stock } j.$ 

$$\rho_{ii} = 1, \rho_{ij} \le 1 \text{ for } i \ne j$$

我们感兴趣的问题是f最大化:

$$f = \max_{x_{ij}y_j} \sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} x_{ij}$$

约束条件:

$$\sum_{i=1}^{n} y_i = q,$$
•  $y_j = 1$  如果选中,否则为0
•  $q$  为基金中股票数量

$$\sum_{j=1}^{n} x_{ij} = 1, \text{ for } i = 1, \dots, n, \quad x_{ij} \le y_j, \text{ for } i = 1, \dots, n; \ j = 1, \dots, n, \quad x_{jj} = y_j, \text{ for } j = 1, \dots, n, x_{ij}, y_j \in \{0, 1\}, \text{ for } i = 1, \dots, n; \ j = 1, \dots, n.$$

 $x_{ij}$ 代表股票 j 跟指数基金中的 i 最相似,如果 j 最相似则为1,否则为0.



### A Hybrid Approach

#### Construct a binary polynomial optimization

From (M) one can construct a binary polynomial optimization with equality constraints only, by substituting the  $x_{ij} \leq y_j$  inequality constraints with the equivalent equality constraints  $x_{ij}(1-y_i)=0$ . Then the problem becomes:

(BPO) 
$$f = \max_{x_{ij}, y_j} \sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} x_{ij}$$

subject to the clustering constraint, the integral constraints, and the following modified consistency constraints:

$$\sum_{j=1}^{n} x_{ij} = 1, \text{ for } i = 1, \dots, n,$$

$$x_{ij}(1 - y_j) = 0, \text{ for } i = 1, \dots, n; j = 1, \dots, n,$$

$$x_{jj} = y_j, \text{ for } j = 1, \dots, n.$$



# Construct the Ising Hamiltonian

We can now construct the Ising Hamiltonian (QUBO) by penalty methods (introducing a penalty coefficient A for each equality constraint) as

$$(IH) \quad H = \sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} x_{ij} + A \left( \sum_{j=1}^{n} y_j - q \right)^2 + \sum_{i=1}^{n} A \left( \sum_{j=1}^{n} x_{ij} - 1 \right)^2 + \sum_{j=1}^{n} A (x_{jj} - y_j)^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} A \left( x_{ij} (1 - y_j) \right).$$



Let us concatenate the decision variables in one vector

$$\mathbf{z} = [x_{11}, x_{12}, \dots, x_{1n}, x_{22}, \dots, x_{nn}, y_1, \dots, y_n],$$

whose dimension is  $\mathbf{z} \in \{0,1\}^N$ , with N = n(n+1) and denote the optimal solution with  $\mathbf{z}^*$ , and the optimal cost  $f^*$ .

In the vector **z**, the Ising Hamiltonian elements can be rewritten as follows,

First term:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} x_{ij} = [\rho_{11}, \rho_{12}, \dots, \rho_{1n}, \rho_{22}, \dots, \rho_{nn} | \mathbf{0}_{n}] \mathbf{z} =: \mathbf{c}_{0}^{T} \mathbf{z}$$

Second term:

$$A\left(\sum_{j=1}^{n} y_j - q\right)^2 = A\left(\sum_{j=1}^{n} y_j\right)^2 - 2Aq\sum_{j=1}^{n} y_j + Aq^2 = A\mathbf{z}^T \left[\frac{\mathbf{0}_{n^2}}{\mathbf{1}_n}\right] \left[\mathbf{0}_{n^2} | \mathbf{1}_n\right] \mathbf{z}$$
$$-2Aq[\mathbf{0}_{n^2} | \mathbf{1}_n] \mathbf{z} + Aq^2 =: \mathbf{z}^T \mathbf{Q}_0 \mathbf{z} + \mathbf{c}_1^T \mathbf{z} + r_0$$



Third term:

$$\sum_{i=1}^{n} A \left( \sum_{j=1}^{n} x_{ij} - 1 \right)^{2} = A \sum_{i=1}^{n} \left( \sum_{j=1}^{n} x_{ij} \right)^{2} - 2A \sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij} + nA =$$

which is equivalent to:

$$= A\mathbf{z}^{T} \left[ \sum_{i=1}^{n} \begin{bmatrix} \mathbf{0}_{n(i-1)} \\ \mathbf{1}_{n} \\ \underline{\mathbf{0}_{n(n-i)}} \\ \mathbf{0}_{n} \end{bmatrix} \begin{bmatrix} \mathbf{0}_{n(i-1)} & \mathbf{1}_{n} & \mathbf{0}_{n(n-i)} & |\mathbf{0}_{n}| \end{bmatrix} \mathbf{z} - 2A[\mathbf{1}_{n}^{2}|\mathbf{0}_{n}]\mathbf{z} + nA \right]$$

$$=: \mathbf{z}^{T} \mathbf{Q}_{1}\mathbf{z} + \mathbf{c}_{2}^{T}\mathbf{z} + r_{1}$$



Fourth term:

$$A \sum_{j=1}^{n-1} (x_{jj} - y_{j})^{2}$$

$$= A\mathbf{z}^{T} \begin{bmatrix} \mathbf{0}_{nj+j} \\ 1 \\ \mathbf{0}_{n^{2}-(nj+j+1)} \\ \mathbf{0}_{j} \\ -1 \\ \mathbf{0}_{n-j-1} \end{bmatrix} \begin{bmatrix} \mathbf{0}_{nj+j} & 1 & \mathbf{0}_{n^{2}-(nj+j+1)} & |\mathbf{0}_{j} & -1 & \mathbf{0}_{n-j-1} \end{bmatrix} \mathbf{z} = A\mathbf{z}^{T} \mathbf{Q}_{2} \mathbf{z}$$



Fifth term:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} A\left(x_{ij}(1-y_j)\right) = A[\mathbf{1}_{n^2}|\mathbf{0}_n]\mathbf{z} + A\mathbf{z}^T \left(\sum_{i=1}^{n} \sum_{j=1}^{n} \begin{bmatrix} \mathbf{0}_{n^2 \times n^2} & -1/2_{(ij,j)} \\ -1/2_{(j,ij)} & \mathbf{0}_n \end{bmatrix}\right)\mathbf{z}$$

$$=: \mathbf{z}^T \mathbf{Q}_3 \mathbf{z} + \mathbf{c}_3^T \mathbf{z}$$

Therefore, the formulation becomes,

$$(IH - QP) \max_{\mathbf{z} \in \{0,1\}^{n(n+1)}} \mathbf{z}^{T} (\mathbf{Q}_{0} + \mathbf{Q}_{1} + \mathbf{Q}_{2} + \mathbf{Q}_{3}) \mathbf{z} + (\mathbf{c}_{0} + \mathbf{c}_{1} + \mathbf{c}_{2} + \mathbf{c}_{3})^{T} \mathbf{z} + r_{0} + r_{1} + r_{2}$$

which can be passed to the variational quantum eigensolver.



# Quantum Computing with IBM Q

For the quantum solution, we use Qiskit. We first define a class QuantumOptimizer that encodes the quantum approach to solve the problem and then we instantiate it and solve it. We define the following methods inside the class:

- exact\_solution: to make sure that the Ising Hamiltonian is correctly encoded in the Z basis, we can compute its eigendecomposition classically, i.e., considering a symmetric matrix of dimension  $2^N \times 2^N$ . For the problem at hand n=3, that is N=12, seems to be the limit for many laptops;
- $vqe\_solution$ : solves the problem (M) via the variational quantum eigensolver (VQE);
- $qaoa_solution$ : solves the problem (M) via a Quantum Approximate Optimization Algorithm (QAOA).



#### 步骤1 & 步骤2

步骤1: 初始化参数

quantum\_optimizer = QuantumOptimizer(rho, n, q)

- the similarity matrix rho;
- the number of assets and clusters n and q;

步骤2: 二值化编码

```
try:
  import cplex
  # warnings.filterwarnings('ignore')
  quantum solution, quantum cost = quantum optimizer.exact solution()
  print(quantum solution, quantum cost)
  classical solution, classical cost = classical optimizer.cplex solution()
  print(classical_solution, classical_cost)
  if np.abs(quantum cost - classical cost) < 0.01:
    print("Binary formulation is correct")
  else:
    print("Error in the formulation of the Hamiltonian")
except Exception as ex:
  print(ex)
```

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### 步骤3: 在Z轴上, 将问题编码为伊辛哈密尔顿量

```
ground_state, ground_level = quantum_optimizer.exact_solution()
print(ground_state)

try:
    if np.abs(ground_level - classical_cost) < 0.01:
        print("Ising Hamiltonian in Z basis is correct")
    else:
        print("Error in the Ising Hamiltonian formulation")
except Exception as ex:
    print(ex)</pre>
```



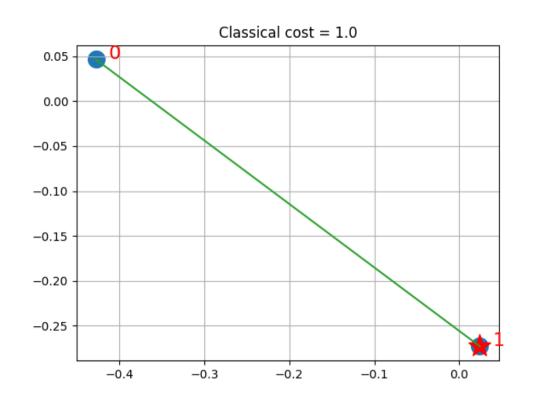
### 步骤4: 通过VQE求解问题

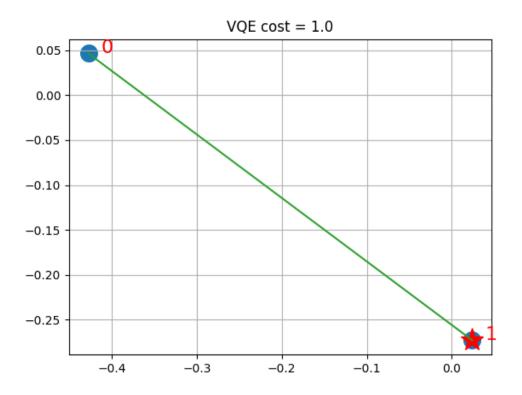
```
vge state, vge level = quantum optimizer.vge solution()
print(vge state, vge level)
try:
  if np.linalg.norm(ground state - vge state) < 0.01:
    print("VQE produces the same solution as the exact eigensolver.")
  else:
    print(
      "VQE does not produce the same solution as the exact eigensolver, but that
is to be expected."
except Exception as ex:
  print(ex)
```

Solve the problem via VQE. Notice that depending on the number of qubits, this can take a while: for 6 qubits it takes 15 minutes on a 2015 Macbook Pro, for 12 qubits it takes more than 12 hours. For longer runs, logging may be useful to observe the workings; otherwise, you just have to wait until the solution is printed.



# 步骤5: 可视化









[1] G. Cornuejols, M. L. Fisher, and G. L. Nemhauser, Location of bank accounts to optimize float: an analytical study of exact and approximate algorithms, Management Science, vol. 23(8), 1997

[2] E. Farhi, J. Goldstone, S. Gutmann e-print arXiv 1411.4028, 2014 <a href="https://arxiv.org/abs/1411.4028">https://arxiv.org/abs/1411.4028</a>

[3] G. Cornuejols and R. Tutuncu, <u>Optimization methods in finance</u>, 2006 <a href="http://web.math.ku.dk/~rolf/CT\_FinOpt.pdf">http://web.math.ku.dk/~rolf/CT\_FinOpt.pdf</a>

[4] DJ. Berndt and J. Clifford, Using dynamic time warping to find patterns in time series. In KDD workshop 1994 (Vol. 10, No. 16, pp. 359-370).

[5] <u>Max-Cut and Traveling Salesman Problem</u>
<a href="https://github.com/Qiskit/qiskit-optimization/blob/main/docs/tutorials/06">https://github.com/Qiskit/qiskit-optimization/blob/main/docs/tutorials/06</a> examples max cut and tsp.ipynb



