

## 介绍



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

#### 本教程包含:

- 1. 投资组合优化 均值方差模型
- 2. 量子算法
- 变分量子本征求解器(VQE)
- 量子近似优化算法 (QAOA)
- 3. 代码实例

#### Qiskit:

https://qiskit.org/documentation/getting\_started.html Qiskit 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/01\_portfolio\_optimization.py https://gitee.com/mymagicpower/qubits/tree/main/quantum\_qiskit\_finance/01\_portfolio\_optimization.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]





本教程给出了给定n个资产,如何解决如下均方差投资组合优化问题的方法:

$$\min_{x \in \{0,1\}^n} qx^T \Sigma x - \mu^T x$$

subject to:  $1^T x = B$ 

- $x \in \{0,1\}^n$  表示 2 值决策变量组成的向量, x[i] = 1表示选取该资产, x[i] = 0表示不选取
- $\mu \in \mathbb{R}^n$  定义期望的资产投资回报率
- $\Sigma \in \mathbb{R}^{n \times n}$  指定资产间的协方差
- q > 0 控制决策者的风险偏好
- B表示预算,例如,从n个资产中选择的资产数量

#### 我们做如下简化假设:

- 所有的资产有同样的价格(归一化为1)
- 全部预算B都投入

约束条件 $1^Tx = B$  是惩罚项 $(1^Tx - B)^2$ 的映射。

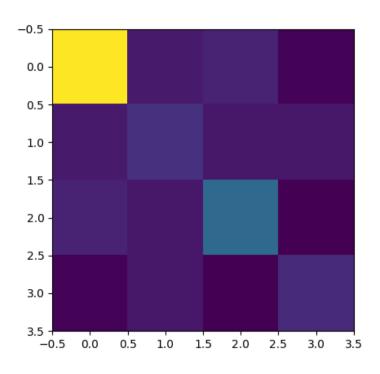
问题结果可以映射为哈密顿量,它的基态代表了最优解。

本教程给出了变分量子本征求解器(VQE),及量子近似优化算法(QAOA)的求解示例,找到给定参数下的最优解。

# 数据初始化



```
# Generate expected return and covariance matrix from
(random) time-series
stocks = [("TICKER%s" % i) for i in range(num assets)]
data = RandomDataProvider(
  tickers=stocks,
  start=datetime.datetime(2016, 1, 1),
  end=datetime.datetime(2016, 1, 30),
  seed=seed,
data.run()
mu = data.get_period_return_mean_vector()
sigma = data.get_period_return_covariance_matrix()
```







```
exact_mes = NumPyMinimumEigensolver()
exact_eigensolver = MinimumEigenOptimizer(exact_mes)
result = exact_eigensolver.solve(qp)
print_result(result)
```

selection	Full result - value	probability
[1 0 0 1] [1 1 1 1] [0 1 1 1] [1 0 1 1] [0 0 1 1] [1 1 0 1] [0 1 0 1] [0 0 0 1] [1 1 1 0] [0 1 1 0]	-0.0149 4.0656 1.0199 1.0049	1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
[1000]	1.0197 -0.0130 1.0208 1.0059 4.0795	0.0000 0.0000 0.0000 0.0000 0.0000

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# 2. 变分量子本征求解器(VQE)

```
from giskit.utils import algorithm globals
algorithm globals.random seed = 1234
backend = Aer.get backend("statevector simulator")
cobyla = COBYLA()
cobyla.set options(maxiter=500)
ry = TwoLocal(num assets, "ry", "cz", reps=3,
entanglement="full")
quantum instance =
QuantumInstance(backend=backend,
seed simulator=seed, seed transpiler=seed)
vge mes = VQE(ry, optimizer=cobyla,
quantum instance=quantum instance)
vqe = MinimumEigenOptimizer(vqe_mes)
result = vqe.solve(qp)
print_result(result)
```

selection	Full result value	probability
	-0.0149	0.8489
$[0\ 0\ 1\ 1]$	-0.0010	0.0885
$[1\ 1\ 0\ 0]$	-0.0130	0.0589
[1010]	-0.0140	0.0018
[0 1 1 0]	0.0008	0.0016
[0 1 0 1]	0.0002	0.0003
[1110]	1.0069	0.0000
$[0\ 0\ 0\ 1]$	1.0191	0.0000
$[0\ 0\ 1\ 0]$	1.0197	0.0000
[0 1 1 1]	1.0199	0.0000
[1000]	1.0059	0.0000
[1 1 0 1]	1.0060	0.0000
[1011]	1.0049	0.0000
[1 1 1 1]	4.0656	0.0000
[0 1 0 0]	1.0208	0.0000
[0 0 0 0]	4.0795	0.0000



# 3. 量子近似优化算法 (QAOA)

```
algorithm globals.random seed = 1234
backend = Aer.get_backend("statevector_simulator")
cobyla = COBYLA()
cobyla.set options(maxiter=250)
quantum instance =
QuantumInstance(backend=backend,
seed_simulator=seed, seed_transpiler=seed)
qaoa_mes = QAOA(optimizer=cobyla, reps=3,
quantum_instance=quantum_instance)
qaoa = MinimumEigenOptimizer(qaoa mes)
result = qaoa.solve(qp)
print_result(result)
```

Full result				
selection	value	probability		
[1001]	-0.0149	0.1683		
[1010]	-0.0140	0.1682		
[1 1 0 0]	-0.0130	0.1679		
$[0\ 0\ 1\ 1]$	-0.0010	0.1654		
[0 1 0 1]	0.0002	0.1652		
[0 1 1 0]	0.0008	0.1650		
[1 1 1 1]	4.0656	0.0000		
[0 0 0 0]	4.0795	0.0000		
[1 1 1 0]	1.0069	0.0000		
[1011]	1.0049	0.0000		
[1 1 0 1]	1.0060	0.0000		
[0 1 0 0]	1.0208	0.0000		
[0 0 1 0]	1.0197	0.0000		
$[0\ 0\ 0\ 1]$	1.0191	0.0000		
[0 1 1 1]	1.0199	0.0000		
[1000]	1.0059	0.0000		





[1] Improving Variational Quantum Optimization using CVaR. Barkoutsos et al. 2019. <a href="https://arxiv.org/abs/1907.04769">https://arxiv.org/abs/1907.04769</a>



