





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

https://qiskit.org/documentation/finance/tutorials/03_european_call_option_pricing.html

本教程包含:

- 1. 欧式看涨期权定价
- 2. 量子算法 通过QAE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

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/03_european_call_option_pricing.py https://gitee.com/mymagicpower/qubits/tree/main/quantum_qiskit_finance/03_european_call_option_pricing.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

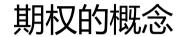
install extra visualization support
For zsh user (newer versions of macOS)
pip install 'qiskit[visualization]'

pip install qiskit[visualization]

安装 Qiskit[finance]

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

pip install qiskit[finance]





期权是一种"选择交易与否的权利"。 如果此权利为"买进"标的物,则称为买权,也称为看涨期权; 如果此权利为"卖出"标的物,则称为卖权,也称为看跌期权。

期权交易的4种策略

- 买入"买权(看涨期权)",(看涨期权多头)
- 卖出"买权(看涨期权)"
- 买入"卖权(看跌期权)"。
- 卖出"卖权(看跌期权)"。

期权的分类

- 欧式期权与美式期权
- 实值期权、平值期权、虚值期权
- 现货期权、期货期权

期权合约要素

- 标的物
- 单位合约数量
- 执行日期(到期日)
- 执行价格(敲定价格)
- 期权买方 (期权多头方)
- 期权卖方 (期权空头方)
- 权利金 (期权费、期权价格)

期权的损益分析



执行价值:期权买方执行期权权利时能获得的利润。 (以欧式期权为例)

• T: 期权到期日。

• S: 现货市价

• K: 成交价

• c: 欧式买权的期权费

• p: 欧式卖权的期权费

期权种类	到期损益
欧式看涨 期权多头	Max { S _T – K – c , - c }
欧式看涨 期权空头	Min { K – S _T + c , + c }
欧式看跌 期权多头	Max { K – S _T – p, - p }
欧式看跌 期权空头	Min { S _T – K + p , + p }

期权的损益分析 - 看涨期权



执行价值:期权买方执行期权权利时能获得的利润。 (以欧式期权为例)

• T: 期权到期日。

• S: 现货市价

• K: 成交价

• c: 欧式买权的期权费 (假定为 0)

期权种类	到期损益
欧式看涨 期权多头	Max { S _T – K, 0 }
欧式看涨 期权空头	Min { K – S _T , 0}

在后面的例子里,量子计算算法基于振幅估计实现,估算到期损益:

$$\mathbb{E}\left[\max\{S_T-K,0\}\right]$$

金融衍生品期权定价的现货市价约束条件:

$$\Delta = \mathbb{P}\left[S_T \geq K\right]$$





在后面的例子里,量子计算算法基于振幅估计实现,估算到期损益:

我们构造一个量子线路,加载对数正态分布(Log-Normal Distribution)数据,初始化量子态。数据分布区间[low,high],使用 2^n 个网格点离散化, n 表示使用的量子位数。幺正变换算子如下:

$$|0\rangle_n \mapsto |\psi\rangle_n = \sum_{i=0}^{2^n-1} \sqrt{p_i} |i\rangle_n,$$

P_i 表示离散分布概率, i为对应正确区间的仿射映射:

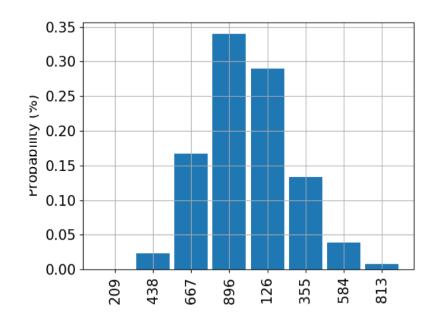
$$\{0,\ldots,2^n-1\} \ni i \mapsto \frac{\operatorname{high}-\operatorname{low}}{2^n-1} * i + \operatorname{low} \in [\operatorname{low},\operatorname{high}].$$



Uncertainty Model

```
# parameters for considered random distribution
S = 2.0 # initial spot price
vol = 0.4 # volatility of 40%
r = 0.05 # annual interest rate of 4%
T = 40 / 365 # 40 days to maturity
# resulting parameters for log-normal distribution
mu = (r - 0.5 * vol**2) * T + np.log(S)
sigma = vol * np.sqrt(T)
mean = np.exp(mu + sigma**2 / 2)
variance = (np.exp(sigma^{**2}) - 1) * np.exp(2 * mu + sigma^{**2})
stddev = np.sqrt(variance)
# lowest and highest value considered for the spot price; in
between, an equidistant discretization is considered.
low = np.maximum(0, mean - 3 * stddev)
high = mean + 3 * stddev
```

```
# construct A operator for QAE for the payoff function by
# composing the uncertainty model and the objective
uncertainty_model = LogNormalDistribution(
    num_uncertainty_qubits, mu=mu, sigma=sigma**2,
bounds=(low, high)
)
```





损益函数 (Payoff Function)

S_T小于等于K时损益函数等于0,然后线性增加。

使用比较器实现,它会交换辅助量子比特: $|0> \rightarrow |1>$, 如果 $S_T>=K$, 该辅助量子比特用于控制损益函数的线性部分。 当 |y| 足够小时:

$$\sin^2(y + \pi/4) \approx y + 1/2$$

因此,对于一个给定的近似缩放因子: $c_{approx} \in [0,1]$ and $x \in [0,1]$

有:
$$\sin^2(\pi/2 * c_{\text{approx}} * (x - 1/2) + \pi/4) \approx \pi/2 * c_{\text{approx}} * (x - 1/2) + 1/2$$

我们使用受控绕Y轴旋转,很容易构造一个算子:

$$|x\rangle|0\rangle \mapsto |x\rangle \left(\cos(a*x+b)|0\rangle + \sin(a*x+b)|1\rangle\right)$$

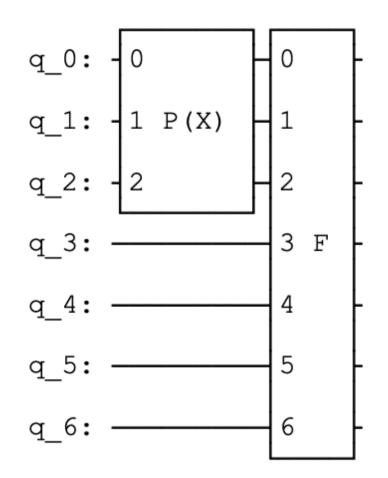
最后,我们需要做的是测量|1>的概率振幅: $\sin^2(a*x+b)$

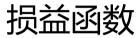
 c_{approx} 越小越准,但是量子位m也需要相应调整。

量子线路 - 初始化



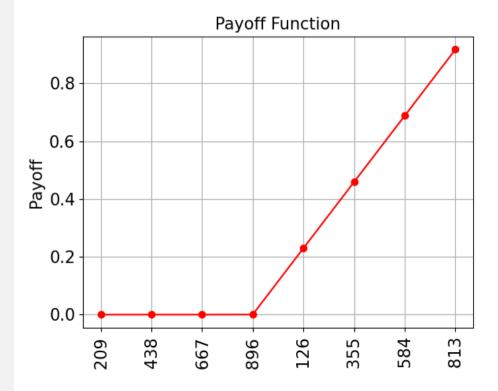
construct A operator for QAE for the payoff function by
composing the uncertainty model and the objective
num_qubits = european_call_objective.num_qubits
european_call = QuantumCircuit(num_qubits)
european_call.append(uncertainty_model,
range(num_uncertainty_qubits))
european_call.append(european_call_objective,
range(num_qubits))







```
# plot exact payoff function (evaluated on the grid of the uncertainty
model)
x = uncertainty model.values
y = np.maximum(0, x - strike price)
plt.plot(x, y, "ro-")
plt.grid()
plt.title("Payoff Function", size=15)
plt.xlabel("Spot Price", size=15)
plt.ylabel("Payoff", size=15)
plt.xticks(x, size=15, rotation=90)
plt.yticks(size=15)
plt.show()
# evaluate exact expected value (normalized to the [0, 1] interval)
exact value = np.dot(uncertainty model.probabilities, y)
exact delta = sum(uncertainty model.probabilities[x >= strike price])
print("exact expected value:\t%.4f" % exact value)
print("exact delta value: \t%.4f" % exact_delta)
```



结果:

exact expected value: 0.1623

exact delta value: 0.8098





```
# set target precision and confidence level
epsilon = 0.01
alpha = 0.05
gi = QuantumInstance(Aer.get backend("aer simulator"),
shots=100)
problem = EstimationProblem(
  state preparation=european call,
  objective qubits=[3],
  post processing=european call objective.post processing,
# construct amplitude estimation
ae = IterativeAmplitudeEstimation(epsilon, alpha=alpha,
quantum instance=qi)
result = ae.estimate(problem)
conf_int = np.array(result.confidence_interval_processed)
print("Exact value: \t%.4f" % exact value)
print("Estimated value: \t%.4f" % (result.estimation processed))
print("Confidence interval:\t[%.4f, %.4f]" % tuple(conf_int))\
```

结果:

Exact value: 0.1623

Estimated value: 0.1665

Confidence interval: [0.1616, 0.1715]





[1] Quantum Risk Analysis. Woerner, Egger. 2018. https://www.nature.com/articles/s41534-019-0130-6

[2] Option Pricing using Quantum Computers. Stamatopoulos et al. 2019. https://quantum-journal.org/papers/q-2020-07-06-291/



