

Problem 2: HHL Algorithm

Problem & Analysis

Solving a linear equation $A * x = b$ in a quantum computational manner, where A is a square matrix and b is a vector with matching dimension. For a simple example:

Solving $Ax = b$ where A is

$$\begin{bmatrix} 1 & 1 \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix}$$

and b is

$$\begin{bmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \end{bmatrix}$$

The solution is unique:

$$\begin{bmatrix} -1/4 \\ 3/4 \end{bmatrix}$$

From linear algebra basics, we know that the solution x might be one from nothing, unique, or an ensemble, depending on the rank of the expanded matrix $[A|b]$. In **any of these cases** noted, we can apply the [Gaussian Elimination](#) method or [Matrix Inversion](#) to get the accurate answer, but naive implementations cost time of $O(n^2)$, while the most optimized classical algorithm reduces it to $O(N\sqrt{k})$, where k describes the cost for inverting the matrix. However, in **case of unique solution**, we have another perspective view and thoughts upon form of the linear equation, where is also probably the [HHL Algorithm](#) derives. 😊

In quantum computation traditions, U denotes a quantum gate and $|\phi\rangle$ denotes a quantum state, when U is applied to $|\phi\rangle$, it turns to be a new state, say $U|\phi\rangle \rightarrow |\psi\rangle$. Corresponding to the physical process that, a quantum system **evolves** its state from $|\phi\rangle$ to $|\psi\rangle$ under the environment influence U . Compared with the linear equation $A * x = b$, it's easy to figure out the logical structure in parallel:

quantum evolution: $U|\phi\rangle \rightarrow |\psi\rangle$

linear equation: $A * x = b$

where U and A are square matrices, others are all vectors in computational representation

i From this view, solving a linear equation is like to **finding the initial state of a quantum evolution process** where the final state is known to be $|\psi\rangle$ while the evolution operator is U . Due to the **reversible computing** nature of quantum computing, this is not a magic in philosophical sense. 😊

Solution

Now it's clear enough to put an elephant into the refrigerator:

- Encode classical A and b to quantum U and $|\psi\rangle$
 - ⚠️ tricky: find ways to satisfy the required unitary & unit vector condition for A and b
- Find $|\phi\rangle$ through matrix inversion of U , aka. computing the reversed $|\phi\rangle = U^\dagger |\psi\rangle$
 - ⚠️ tricky: do not inverse U directly, but instead decompose $|\psi\rangle$ to U 's eigen vectors, then simply inverse the eigen values 😊
- Decode $|\phi\rangle$ to get the solution x (in a probabilistic approximated sense)

Assuming the toy case $\dim(A) = \text{rank}(A) = 2$, we implement & explain the HHL algorithm in both mathematic and programmatic view in following sections.

HHL in a mathematic view

Firstly, here's the mathematic formula tour sketch:

Our goal is to approximate this state $|x\rangle$:

```
A|x> = |b> // assume A is an invertible hermitian (no need be unitary), and |b> is a unit vector
|x> = A^(-1) |b>
    = Σ_i 1/λ_i |v_i><v_i| |b> // eigen decomposition of A^(-1) where λ_i and |v_i> are the i-th eigen pair
    = (Σ_i 1/λ_i |v_i><v_i|) (Σ_j β_j |v_j>) // decompose |b> to A's eigen basis |v_i>; i,j ∈ [0, N-1], N = dim(A)
    = Σ_i Σ_j β_j / λ_i |v_i><v_i|v_j>
    = Σ_i Σ_j β_j / λ_i |v_i> // <v_i|v_j> == 1 if i==j else 0
    = Σ_i (Σ_j β_j) 1/λ_i |v_i> // aggregate inner const coeffs
    = Σ_i β_i / λ_i |v_i> // rename, β_i only depends on i
```

Firstly, consider estimating eigvals of A over vector $|b\rangle$, using two ancilla qubits inited as $|00\rangle$:

```
= QPE_2(A, |00b>)
= C_02(U^2^1) * C_12(U^2^0) * (H @ H @ I) |00b> // |q0,q1,q2>, C_ij(U) denotes controlled-unitary U on |qi>
= C_02(U^2) * C_12(U) * |++b> // |++> = H|0>, θ_k for q[k-1]
= C_02(U^2) * C_12(U) * |++(|0>+|1>)|b> // ignore global phase
= C_02(U^2) * |++(|0b>+|1>U|b>)
= C_02(U^2) * (|0>+|1>)(|0b>+|1>U|b>)
= C_02(U^2) * (|00b> + |01>U|b> + |10b> + |11>U|b>)
= |00b> + |01>U|b> + |10>U^2|b> + |11>U^3|b>
= (Σ_k |k> U^k) |b> // <= how to choose U, then reduce U^k|b> ??
```

let $U = \exp(iAt) = \sum_j \exp(i\lambda_j t) |v_j\rangle\langle v_j|$ where t is a tunable parameter (eg. 2π), now U is unitary since A

```
= (Σ_k |k> exp(iAt)^k) |b>
= (Σ_k |k> exp(iAtk)) |b>
= (Σ_k |k> exp(iAtk) |v_j><v_j|) |b> // again decompose |b>, U has the same eigvecs with A
= (Σ_k |k> exp(iAtk) |v_j><v_j|) (Σ_i β_i |v_i>) // <v_i|v_j> == 1 if i==j else 0
= Σ_k |k> (Σ_j β_j exp(iAtk) |v_j>)
= Σ_j β_j (Σ_k |k> exp(iAtk)) |v_j> // law of commutativity
= Σ_j β_j (Σ_k |k> (Σ_s exp(iλ_s t) |v_s><v_s|)) |v_j>
= Σ_j β_j (Σ_k |k> exp(iλ_j t k)) |v_j> // <v_s|v_j> == 1 if s==j else 0
= Σ_j β_j (Σ_k exp(iλ_j t k) |k>) |v_j> // law of commutativity for a scalar
= Σ_j β_j |λ_j'> |v_j> // FIXME: jump of faith following the standard QPE??
```

where λ_j' is the n -qubit binary approximation to $2^n(\lambda_j t / 2\pi)$, while λ_j is the real eigvals, i.e.:

$$\lambda_j' = 2^n * (\lambda_j t) / (2\pi)$$

see in order to let λ_j' to approximate the true λ_j , we will need:

$$1 = 2^n * t / (2\pi)$$

$$t = 2\pi / 2^n$$

when $n = 2$ in our case, the t (or in hamilton-simulation namely t_0) should be:

$$t = 2\pi / 2^2$$

$$= \pi/2$$

Now, compare what we've got:

$$|z\rangle = \sum_i \beta_i |\lambda_i'\rangle |v_i\rangle$$

and what we'd want:

$$|x\rangle = \sum_i \beta_i / \lambda_i |v_i\rangle$$

it would be nicely approximated, if we can:

- move the index value λ_j' out from the auxiliary register $|\lambda_j'\rangle$
- turn it to become the proper coefficient $1/\lambda_i$

Following the thesis, adding an extra ancilla qubit $|q0\rangle$ inited with $|1\rangle$,

then this $|\lambda_i\rangle$ needs an RY rotation of angle $\theta_j = -2\arcsin(C/\lambda_j)$, controlled by the ancilla qubit

where C is a normalizer constant holding that $C \leq \min(\lambda_j)$:

$$\begin{aligned} &= CR(|0, z\rangle, C) \\ &= C_{02}(RY(\theta_1)) * C_{01}(RY(\theta_2)) * (X @ I @ I) |0, z\rangle \quad // |q_0, q_1, q_2, q_3\rangle, C_{ij}(U) \text{ denotes controlled-unitary } U \text{ on } \\ &= C_{02}(RY(\theta_1)) * C_{01}(RY(\theta_2)) |1\rangle (\sum_i \beta_i |\lambda_i'\rangle |v_i\rangle) \\ &= \sum_j (\sqrt{1-(C/\lambda_j)^2} |0\rangle + C/\lambda_j |1\rangle) \beta_i |\lambda_i'\rangle |v_j\rangle \end{aligned}$$

hence when the ancilla bit is measured to be $|1\rangle$, the $|q_3\rangle$ would be in state:

$$\begin{aligned} &= \sum_j (C/\lambda_j) \beta_i |v_j\rangle \\ &= \sum_j C \beta_i / \lambda_j |v_j\rangle \end{aligned}$$

when we let $C = 1$, the state matches what we exactly want :)

For conveniently gathering results, iQPE can be performed to sort the outgoing vector:

$$\begin{aligned} &= (I @ iQPE_2(A, |00b\rangle)) * CR(|0, z\rangle, C) \\ &= (I @ iQPE_2(A, |00b\rangle)) * \sum_j (\sqrt{1-(C/\lambda_j)^2} |0\rangle + C/\lambda_j |1\rangle) \beta_i |\lambda_i'\rangle |v_j\rangle \\ &= \sum_j (\sqrt{1-(C/\lambda_j)^2} |0\rangle + C/\lambda_j |1\rangle) |00\rangle |v_j\rangle \end{aligned}$$

which restores the QPE register $|q_1 q_2\rangle$ to $|00\rangle$

Finally, amplitude values at 0 and $2^{*}3$ are the answer.

We are done. 😊

HHL in a programmatic view

And here's the pseudo-code sketch for the procedure framework:

```
def HHL(A:Matrix, b:Vector) -> Vector:
    # Step 1: classical preprocess
    (Ah, b_n), stats = transform(A, b)    # transform to `Ah * y = b_n`

    # Step 2: quantum computing
    cq = HHL_circuit(Ah, b_n)            # build qcircuit
    qstate = qvm.run(cq)                  # run and get the final state vector
    y = project_q3(qstate)                # only need amplitude of |q3>

    # Step 3: classical postprocess
    x = transform_inv(y, *stats)          # transform back to get `x`

    return x
```

Components are explained in following sections.

○ Transform the equation

To make the quantum evolution framework work, it requires A to be **hermitian** while b to be a **normalized vector**. However, A and b are **arbitrarily** given from a linear equation. Follow this to transform an arbitrary linear equation to suit valid quantum gate and state:

```

Ax = b
(A'A) x = A'*b      # multiply by A' (A.dagger) at both sides, assert A'A is her
(A'A) (x / |A'*b|) = A'*b / |A'*b| # divide by |A'*b| at both sides, assert right side is unit
A_h * y = b_n        # rename, now this new equation satisfies all needed conditions

```

It is easy to inverse the transformation back later, in order to get the final answer:

```

x / |A'*b| = y
x = y * |A'*b|      # the final answer

```

Take the concrete question as example:

```

Ax = b
=>
[ 1, 1] = [ 1/ 2]
[1/√2, -1/√2] x = [-1/√2]
=>
[1, 1/√2][ 1, 1] = [1, 1/√2][ 1/ 2]
[1, -1/√2][1/√2, -1/√2] x = [1, -1/√2][-1/√2]
=>
[3/2, 1/2] = [0]
[1/2, 3/2] x = [1]
=>
A12 x = |1>

```

It turns out to be the equation that many essays have long played with: $A_{12} x = |1\rangle$ where A_{12} is a hermitian matrix with eigvals 1 and 2. 😊

○ Encode quantum data

Find the circuits to encode the classical data to quantum facts $U = \exp(iA\theta)$ and

$|b\rangle = b_0|0\rangle + b_1|1\rangle$:

```

def encode_A(A:Matrix, θ:float) -> QGate:
    ''' encode a hermitian A to unitary exp(iAθ) '''
    assert is_hermitian(A)
    u = scipy.linalg.expm(1j*A*θ)      # matrix exponential, turning to be a unitary for hermitian
    assert is_unitary(u)
    return QOracle(u)                  # make an Oracle gate, or `matrix_decompose()` to U4 gates

def encode_b(b:Vector) -> QCircuit:
    ''' encode a unit vector b onto amplitude of |b> '''
    assert is_unit(b)
    θ = 2 * np.arccos(b[0])
    cq = QCircuit() << RY(θ)           # rotate with RY gate
    if b[1] < 0: cq << Z()              # fix the sign of |1> part
    return cq

```

i Parameters for these gates are manually calculated out according to [matrix form definition](#), this is unnatural but on its way...

⚠ The function `encode_A()` shown here is a conceptual demo, we need U^{2^k} rather than simple U in QPE, see real code for the details. 😞

○ Main circuit routine

Construct the main circuit routine as HHL requires: QPE, controlled RY rotation and iQPE.

```

def HHL_circuit(A:Matrix, b:Vector, t0=2*pi, r=4) -> QCircuit:
    # q0: perform RY to inverse  $\lambda_i$ 
    # q1~q2: QPE scatter  $A \Rightarrow \sum |\lambda_i\rangle$ ,  $\lambda_i$  is integer approx to eigvals of A
    # q3: amplitude encode  $b \Rightarrow |b\rangle$ 
    q0, q1, q2, q3 = list(qvm.qAlloc_many(4))    # work around of tuple unpack

    # Step 1: prepare  $|b\rangle$ , very toyish :(
    enc_b = encode_b(b, q3)

    # Step 2: QPE of A over  $|b\rangle$ 
    # following the approx formula:  $\lambda_j' = 2^n * (\lambda_j * t) / (2 * \pi)$ 
    # in order to let  $\lambda_j' = \lambda_j$ , we have  $t = 2 * \pi / 2^n = \pi / 2$ 
    t = 2*pi / 2**2
    qpe = QCircuit() \
        << H([q1, q2]) \
        << encode_A(A, q3, t, 0, QOracle).control(q2) \
        << encode_A(A, q3, t, 1, QOracle).control(q1) \
        << H(q1) \
        << CR(q1, q2, pi/2).dagger() \
        << H(q2)

    # Step 3: controlled-Y rotate  $\theta_j = 2 * \arcsin(C / \lambda_i) \approx 2 * C / \lambda_i$ ;  $2^{(1-r)} * \pi = 2 * C$ 
    # NOTE: the rotation angles are accordingly esitimated by eigvals of A
    # note that  $RY(\theta)|1\rangle = [ \quad // \text{the more } \theta \text{ it rotates, the more away from } |1\rangle \text{ and shifts to } |0\rangle$ 
    #   -sin( $\theta/2$ ),
    #   cos( $\theta/2$ ),
    # ]
    eigenvals, eigenvecs = npl.eig(A)
    lbd1, lbd2 = sorted(eigenvals)
    C = lbd1    # C is a normalizer being  $C \leq \min(\lambda_i)$ 
    # we starts ancilla qubit from  $|1\rangle$ , so add a sign to rotation angle  $\theta_j$ 
    cr = QCircuit() \
        << X(q0) \
        << RY(q0, -2*np.arcsin(C/lbd1)).control(q1) \
        << RY(q0, -2*np.arcsin(C/lbd2)).control(q2)

    return enc_b << qpe << cr << qpe.dagger()

```

HHL in a programmatic view (further optimizations and tricks)

However, as an application, this 4-qubits circuit we've just proposed indeed suffers from heavy **precision problems**, due to its very limited resource -- only two qubits -- in the QPE process. Raising the consequences:

- It cannot handle input matrix with eigvals that hard to approximate within 2-qubits
- It heavily relies on the `qOracle` gate, when replaced by `matrix_decompose()`, precision drops dramatically

To make somebody happy, we further introduce two cheaty technics responding to the issues above respectively.

- Apply the `reduce` preprocessing rather than that in former section, this will reduces any other arbitrary matrix A to our well-known A_{12} toy in all essays, assuring no eigval estimation loss during 2-qubit QPE process.
- Since we've fixed the input A to be a certain A_{12} , we manually do the matrix decomposition to break `QOracle` gate down to `U4` and `X` gates

See these in source code for implementation details~

Source Code

⚠ The whole source code is extremely long (~900 lines), as we've did a lot of fruitless experiments and explorations. Here we only paste the finally working parts. 😂

Tested under `pyqpanda 3.7.12 + Python 3.8.15`


```

#!/usr/bin/env python3
# Author: Armit
# Create Time: 2023/04/03

from typing import Tuple, List, Callable, Union

from pyqpanda import *
import numpy as np
np.set_printoptions(suppress=True, precision=7)
import numpy.linalg as npl
import scipy.linalg as spl

Matrix = np.ndarray
Vector = np.ndarray

# case of the special: `A12` is the original essay example, `b1` is the test case from Qiskit cc
# NOTE: Aij is required to be hermitian (not needed to be unitary though)
r2 = np.sqrt(2)
pi = np.pi
A12 = np.asarray([      # eigval: 2, 1
    [3, 1],             # eigvec: [0.70710678, 0.70710678], [-0.70710678, 0.70710678]
    [1, 3],
]) / 2
b1 = np.asarray([0, 1]) # |b> = |1>

# case of the target `question1()`
# svd(A) = P * D * Q
# [-1 0][1 0][-1 -1]
# [ 0 1][0 1/r2][ 1 -1]
A = np.asarray([      # eigval: 1.34463698, -1.05174376
    [ 1, 1],           # eigvec: [0.9454285, 0.32582963], [-0.43812257, 0.89891524]
    [1/r2, -1/r2],
])
b = np.asarray([
    1/2,
    -1/r2,
])

def project_q3(qstate:List[complex], is_first:bool=False) -> List[complex]:
    ''' gather all cases of ancilla qubit to be |1>, then pick out the target |q> only '''

    if is_first:
        # the first |q0> is the target qubit
        return qstate[len(qstate)//2][:2]
    else:
        # the last |q3> is the target qubit
        return [qstate[0], qstate[len(qstate)//2]]

```

```

def transform(A:Matrix, b:Vector, meth:str='hermitian', A_r:Matrix=A12) -> Tuple[Tuple[Matrix, \
    ''' Transforming an arbitray  $Ax = b$  to equivalent forms '''

    assert meth in ['reduce', 'hermitian']

    if meth == 'reduce':
        '''
            Reduce arbitray  $Ax = b$  to  $Ar * y = b_n$  where  $Ar$  is hand-crafted well-known and  $b_n$  is unit
                 $A * x = b$ 
                 $(Ar * D) * x = b$  # left-decompose A by a known matrix Ar, this is NOT effec
             $Ar * (D / |b| * x) = b / |b|$  # normalize right side b, turining it a unit vector
                 $Ar * y = b_n$  # rename, suits the form required by HHL_2x2 circuit
        '''
        D = npl.inv(A_r) @ A
        b_norm = npl.norm(b)
        b_n = b / b_norm

        # the validated A and b for new equation, and stats needed for inversion
        return (A_r, b_n), (D, b_norm)

    if meth == 'hermitian':
        '''
            Multiply a certain B on both side to make A a hermitian, then :
                 $A * x = b$ 
                 $(A' * A) * x = A' * b$  # (if necessary) multiply by A.dagger a
             $(A' * A) * (x / |A' * b|) = (A' * b) / |A' * b|$  # normalize right side  $A' * b$ , turining
                 $Ah * y = b_n$  # rename, suits the form required by H-
        '''

        if not np.allclose(A, A.conj().T): # if A is not hermitian, make it hermitian
            B = A.conj().T #  $A' * A$  is promised to be hermitian in math
            A_h = B @ A
            b_n = B @ b
            assert np.allclose(A_h, A_h.conj().T)
        else:
            A_h = A

        b_norm = npl.norm(b)
        b_n = b / b_norm

        # the validated A and b for new equation, and stats needed for inversion
        return (A_h, b_n), (None, b_norm)

def transform_inv(y:Vector, D:Matrix, b_norm:float, meth:str='hermitian') -> Vector:
    ''' Solve x from transformed answer y '''

    assert meth in ['reduce', 'hermitian']

    if meth == 'reduce':
        '''
            Solve x from  $y = D / |b| * x$ , this is NOT effecient in any sense though:

```

```

        D / |b| * x = y
        x = (D / |b|)^(-1) * y
        x = D^(-1) * |b| * y
    ...

    return npl.inv(D) @ (b_norm * y)

if meth == 'hermitian':
    ...
    Solve x from y = x / |A' * b|:
    x / |A' * b| = y
    x = |A' * b| * y
    ...

    return y if abs(1.0 - b_norm) < 1e-5 else b_norm * y

def encode_b(b:Vector, q:Qubit) -> QCircuit:
    ...
    Amplitude encode a unit vector b = [b0, b1] to |b> = b0|0> + b1|1> use RY+Z gate,
    to fix the lacking the coeff `e^(i*phi)` compared with U3 gate when b1 < 0
        RY(theta) |0> = |b>
    [cos(theta/2), -sin(theta/2)][1] = [b0]
    [sin(theta/2), cos(theta/2)][0] = [b1]
    ...
    if isinstance(b, list): b = np.asarray(b)
    assert isinstance(b, Vector), 'should be a Vector/np.ndarray'
    assert tuple(b.shape) == (2,), 'should be a vector lengthed 2'
    assert (npl.norm(b) - 1.0) < 1e-5, 'should be a unit vector'

    theta = 2 * np.arccos(b[0])
    cq = QCircuit() << RY(q, theta)
    if b[1] < 0: cq << Z(q) # fix sign of |1> part

    return cq

def encode_A(A:Matrix, q:Qubit, theta:float=2*pi, k:float=0, encoder=QOracle) -> Union[QGate, QCircuit]:
    ''' Unitary generator encode hermitian A to a unitary up to power of 2: U^2^k = exp(iAθ)^2^k '''
    assert isinstance(A, Matrix), 'should be a Matrix/np.ndarray'
    assert tuple(A.shape) == (2, 2), 'should be a 2x2 matrix'
    assert np.allclose(A, A.conj().T), 'should be a hermitian matrix'
    assert encoder in [QOracle, matrix_decompose]

    u = spl.expm(1j * A * theta).astype(np.complex128) # FIXME: explain why this is a valid unitary
    assert np.allclose(u @ u.conj().T, np.eye(len(u)))

    return encoder(q, npl.matrix_power(u, 2**k).flatten())

def HHL_2x2_qpanda_5(A:Matrix=A12, b:Vector=b1, enc:str='oracle') -> QCircuit:
    ''' The guessed implementations from QPanda HHLAlg print(circuit) using 5-qubits '''

```

```

# q0: |b>
# q1~3: QFT (leave 1 for sign?? do not know why...)
# q4: ancilla
qv = qvm.qAlloc_many(5)
q0, q1, q2, q3, q4 = [qv[i] for i in range(len(qv))]

# HHLAlg uses RY to encode
enc_b = QCircuit() << RY(q0, 2*np.arccos(b[0]))

# FIXME: when QOracle be replaced with `matrix_decompose()`, precision drops dramatically
t = 2*pi / (1<<3)      # theta = 2*pi / (1<<n_qft)
encoder = QOracle if enc == 'oracle' else matrix_decompose
qpe = QCircuit() \
    << H([q1, q2, q3]) \
    << encode_A(A, q0, t, 0, encoder).control(q3) \
    << encode_A(A, q0, t, 1, encoder).control(q2) \
    << encode_A(A, q0, t, 2, encoder).control(q1) \
    << H(q1) \
    << CR(q1, q2, pi/2).dagger() \
    << CR(q1, q3, pi/4).dagger() \
    << H(q2) \
    << CR(q2, q3, pi/2).dagger() \
    << H(q3)

cr = QCircuit() \
    << X([q2, q3]) \
    << RY(q4, pi).control([q1, q2, q3]) \
    << X([q1, q2]) \
    << RY(q4, pi/3).control([q1, q2, q3]) \
    << X([q3]) \
    << RY(q4, -pi/3).control([q1, q2, q3]) \
    << X([q1]) \
    << RY(q4, -pi).control([q1, q2, q3])

return enc_b << qpe << cr << qpe.dagger()

def HHL_2x2_ours(A:Matrix=A12, b:Vector=b1, enc:str='oracle', rot:str='eigval') -> QCircuit:
    ...

    My modified version, looking for best param according to Qiskit:
    - https://qiskit.org/textbook/ch-applications/hhl\_tutorial.html
    - https://arxiv.org/pdf/2108.09004.pdf
    ...

    assert np.allclose(A, A.conj().T), 'A should be a hermitian'
    assert (np.linalg.norm(b) - 1.0) < 1e-5, 'b should be a unit vector'
    assert enc in ['oracle', 'decompose', 'hard-coded']
    assert rot in ['eigval', 'approx']

# q0: perform RY to inverse λi
# q1~q2: QPE scatter A => Σ|λi>, λi is integer approx to eigvals of A

```

```

# q3: amplitude encode b => |b>
qv = qvm.qAlloc_many(4)
q0, q1, q2, q3 = [qv[i] for i in range(len(qv))]

# Step 1: prepare |b>, very toyish :(
enc_b = encode_b(b, q3)

# Step 2: QPE of A over |b>
# following the approx formula:  $\lambda_j' = 2^n * (\lambda_j * t) / (2 * \pi)$ 
# in order to let  $\lambda_j' = \lambda_j$ , we have  $t = 2 * \pi / 2^n * \text{qft} = \pi / 2$ 
t = 2 * pi / 2 ** 2

if enc == 'oracle':
    u2 = encode_A(A, q3, t, 0, QOracle)
    u1 = encode_A(A, q3, t, 1, QOracle)
if enc == 'decompose':
    u2 = encode_A(A, q3, t, 0, matrix_decompose)
    u1 = encode_A(A, q3, t, 1, matrix_decompose)
if enc == 'hard-coded':
    # The actual  $U(iA\theta)$  for  $A=A_{12}$ ,  $\theta=\pi/2$  is:
    #  $\begin{bmatrix} -1+i & -1-i \\ -1-i & -1+i \end{bmatrix} / 2$ 
    # the  $U(iA\theta)^{2^0}$  is the same as above, it can be decomposed as U4 and X
    # and the  $U(iA\theta)^{2^1}$  is actually X gate, nice ;)
    u2 = QCircuit() << X(q3) << U4(-0.75*pi, -pi/2, pi/2, pi/2, q3)
    u1 = X(q3)

qpe = QCircuit() \
    << H([q1, q2]) \
    << u2.control(q2) \
    << u1.control(q1) \
    << H(q1) \
    << CR(q1, q2, pi/2).dagger() \
    << H(q2)

# Step 3: controlled-Y rotate  $\theta_j = 2 * \arcsin(C/\lambda_i) \approx 2 * C/\lambda_i$ ;  $2^{(1-r)} * \pi = 2 * C$ 
# note that  $RY(\theta)|1\rangle = \begin{bmatrix} \cos(\theta/2) \\ -\sin(\theta/2) \end{bmatrix}$  // the more  $\theta$  it rotates, the more away from  $|1\rangle$  and shifts to  $|0\rangle$ 
#  $\begin{bmatrix} \cos(\theta/2) \\ -\sin(\theta/2) \end{bmatrix}$ 
# ]
# we starts ancilla qubit from  $|1\rangle$ , so add a sign to rotation angle  $\theta_j$ 

if rot == 'eigval':
    # the rotation angles are accordingly esitimated by eigvals of A
    eigenvals, eigenvecs = npl.eig(A)
    lbd1, lbd2 = sorted(eigenvals)
    C = lbd1 # C is a normalizer being  $C \leq \min(\lambda_i)$ 
    r1 = -2 * np.arcsin(C/lbd1)
    r2 = -2 * np.arcsin(C/lbd2)
if rot == 'approx':
    # the rotation angles are generally approximated

```

```

# for big endian  $|q_1q_2\rangle$ ,  $|00\rangle=0.0$ ,  $|10\rangle=0.25$ ,  $|01\rangle=0.5$ ,  $|11\rangle=0.75$ 
r1 = -pi
r2 = -pi/3

cr = QCircuit() \
    << X(q0) \
    << RY(q0, r1).control(q1) \
    << RY(q0, r2).control(q2)

return enc_b << qpe << cr << qpe.dagger()

def HHL(A:Matrix, b:Vector, HHL_cq:Callable, HHL_cq_args:tuple=tuple(), meth:str='hermitian', pr
...
    Solving linear system equation  $Ax = b$  by quantum simulation in  $\text{poly}(\log N)$  steps
    - https://arxiv.org/abs/0811.3171
    - https://arxiv.org/abs/2108.09004
    - https://arxiv.org/abs/1110.2232
    - https://arxiv.org/abs/1302.1210
    - https://arxiv.org/abs/1805.10549
    - https://arxiv.org/abs/1302.4310
    - https://arxiv.org/abs/1302.1946
    - https://en.wikipedia.org/wiki/Quantum\_algorithm\_for\_linear\_systems\_of\_equations
    - https://zhuanlan.zhihu.com/p/164375189
    - https://zhuanlan.zhihu.com/p/426811646
    - https://www.qtumist.com/post/5212
    - https://pyqpanda-tutorial.readthedocs.io/zh/latest/HHL.html
    NOTE:
    - Input  $A$  and  $b$  for this function are arbitrary, they will be auto-transformed for vali
    - Due to resource limit of 4 qubits and explorations of our ancestors, we do NOT solve art
      but only solve one special prototype case in quantum manner, then **reduce** any other c
      This special case is artificially designed to allow eigenvals of matrix A is stored with
      i.e. we choose a unitary A with eigen values of [1, 2], [1, 3] or [2, 3], so that eigenv
...
assert isinstance(A, Matrix) and tuple(A.shape) == (2, 2)
assert isinstance(b, Vector) and tuple(b.shape) == (2,)

# Step 1: transform in a classical manner
(Ar, b_n), stats = transform(A, b, meth=meth)

# Step 2: solving  $Ar * y = b_n$  in a quantum manner
global qvm
qvm = CPUQVM()
qvm.init_qvm()

hhl_cq = HHL_cq(Ar, b_n, *HHL_cq_args)

prog = QProg() << hhl_cq
qvm.directly_run(prog)
y = project_q3(qvm.get_qstate(), is_first=HHL_cq is HHL_2x2_qpanda_5)

```

```

ircode = ''
if prt_ircode:
    try: ircode = to_originir(prog, qvm)
    except: pass
#qvm.qFree_all(qvm.get_allocate_qubits()) # FIXME: buggy, stuck to SEGV
qvm.finalize()

# Step 3: inv-transform in a classical manner
y = np.asarray(y, dtype=np.complex128)
x = transform_inv(y, *stats, meth=meth)
x = x.real.tolist()

if prt_ircode:
    return x, ircode
else:
    return x

def question1() -> Tuple[list, str]:
    return HHL(A, b, HHL_2x2_ours, ('hard-coded', 'approx'), meth='hermitian', prt_ircode=True)

def benchmark(kind:str, eps=1e-2):
    circuits = [
        'ours',
        'qpanda_5',
    ]

    v_errors = [0.0] * len(circuits) # error of value L2
    n_errors = [0.0] * len(circuits) # error up to a normalization

    for _ in range(1000):
        if kind == 'random':
            A_ = np.random.uniform(size=[2, 2], low=-1.0, high=1.0)
            b_ = np.random.uniform(size=[2], low=-1.0, high=1.0)
        elif kind == 'target': # around target case
            A_ = A + np.random.uniform(size=[2, 2], low=-1.0, high=1.0) * eps
            b_ = b + np.random.uniform(size=[2], low=-1.0, high=1.0) * eps
        else: raise ValueError

        try:
            z = npl.solve(A_, b_)
            z_n = z / npl.norm(z)
        except npl.LinAlgError:
            continue

        for i, name in enumerate(circuits):
            x = HHL(A_, b_, globals()['HHL_2x2_' + name], meth='hermitian')
            v_errors[i] += npl.norm(np.abs(z - np.asarray(x)))
            x_n = x / npl.norm(x)
            n_errors[i] += npl.norm(np.abs(z_n - x_n))

```

```

for i, name in enumerate(circuits):
    print(f' {name}: {v_errors[i]} / {n_errors[i]}')

def run_compares(A:Matrix, b:Vector, title='case'):
    print(f'{title}')
    print(' truth: ', npl.solve(A, b))
    print(' ours (r+hc+a): ', HHL(A, b, HHL_2x2_ours, ('hard-coded', 'approx'), meth='reduce'))
    print(' ours (r+hc+e): ', HHL(A, b, HHL_2x2_ours, ('hard-coded', 'eigval'), meth='reduce'))
    print(' ours (r+d+a): ', HHL(A, b, HHL_2x2_ours, ('decompose', 'approx'), meth='reduce'))
    print(' ours (r+d+e): ', HHL(A, b, HHL_2x2_ours, ('decompose', 'eigval'), meth='reduce'))
    print(' ours (r+o+a): ', HHL(A, b, HHL_2x2_ours, ('oracle', 'approx'), meth='reduce'))
    print(' ours (r+o+e): ', HHL(A, b, HHL_2x2_ours, ('oracle', 'eigval'), meth='reduce'))
    print(' ours (h+hc+a): ', HHL(A, b, HHL_2x2_ours, ('hard-coded', 'approx'), meth='hermitian'))
    print(' ours (h+hc+e): ', HHL(A, b, HHL_2x2_ours, ('hard-coded', 'eigval'), meth='hermitian'))
    print(' ours (h+d+a): ', HHL(A, b, HHL_2x2_ours, ('decompose', 'approx'), meth='hermitian'))
    print(' ours (h+d+e): ', HHL(A, b, HHL_2x2_ours, ('decompose', 'eigval'), meth='hermitian'))
    print(' ours (h+o+a): ', HHL(A, b, HHL_2x2_ours, ('oracle', 'approx'), meth='hermitian'))
    print(' ours (h+o+e): ', HHL(A, b, HHL_2x2_ours, ('oracle', 'eigval'), meth='hermitian'))
    print(' qpanda_5 (h+d): ', HHL(A, b, HHL_2x2_qpanda_5, ('decompose',), meth='hermitian'))
    print(' qpanda_5 (h+o): ', HHL(A, b, HHL_2x2_qpanda_5, ('oracle',), meth='hermitian'))
    print(' qpanda_alg: ', np.asarray(HHL_solve_linear_equations((A.conj().T @ A).astype(np.cc
    print()

if __name__ == '__main__':
    # solve the specified target linear equation
    run_compares(A, b, '[target question]')

    # benchmark error of different circuits
    print('[benchmark random] L1 error / L1 error after norm:')
    benchmark(kind='random')
    print('[benchmark target] L1 error / L1 error after norm:')
    benchmark(kind='target', eps=1e-2)
    print()

    # solve random linear equations
    A = np.random.uniform(size=[2, 2], low=-1.0, high=1.0)
    b = np.random.uniform(size=[2], low=-1.0, high=1.0)
    run_compares(A, b, '[random question]')
    print()

    # test the question API
    _, ircode = question1()
    print(ircode)

```

Run demo:


```
C:\Windows\system32\cmd.exe
```

```
D:\Desktop\Workspace\quantum-computation-playground\contest\第二
-> py P2_partial.py
[target question]
truth: [-0.25  0.75]
ours (r+hc+a): [-0.24999999999999999, 0.75000000000000003]
ours (r+hc+e): [-0.24999999999999999, 0.75000000000000003]
ours (r+d+a): [-0.2520000636763246, 0.5407413518849395]
ours (r+d+e): [-0.2520000636763246, 0.5407413518849395]
ours (r+o+a): [-0.25000000000000001, 0.75000000000000004]
ours (r+o+e): [-0.25000000000000001, 0.75000000000000004]
ours (h+hc+a): [-0.25000000000000003, 0.75000000000000003]
ours (h+hc+e): [-0.25000000000000003, 0.75000000000000003]
ours (h+d+a): [-0.02368358637268825, 0.6798946985944283]
ours (h+d+e): [-0.02368358637268825, 0.6798946985944283]
ours (h+o+a): [-0.25000000000000006, 0.75000000000000004]
ours (h+o+e): [-0.25000000000000006, 0.75000000000000004]
qpanda_5 (h+d): [-0.14295193903749967, -5.151865880056138e-17]
qpanda_5 (h+o): [-0.25000000000000044, 0.7500000000000008]
qpanda_alg: [-0.25  0.75]

[benchmark random] L1 error / L1 error after norm:
ours: 5745.543476354065 / 925.6926510649588
qpanda_5: 5818.389604480754 / 1130.4593937177713
[benchmark target] L1 error / L1 error after norm:
ours: 7.635097241276007 / 0.26757021666853165
qpanda_5: 7.610073790804623 / 4.67870170333206

[random question]
truth: [-0.8085786 -1.5551322]
ours (r+hc+a): [-0.8085786174566512, -1.5551321559982882]
ours (r+hc+e): [-0.8085786174566512, -1.5551321559982885]
ours (r+d+a): [-0.43063826232304275, -1.3670488119830915]
ours (r+d+e): [-0.43063826232304286, -1.3670488119830912]
ours (r+o+a): [-0.8085786174566512, -1.5551321559982885]
ours (r+o+e): [-0.8085786174566512, -1.5551321559982885]
ours (h+hc+a): [-0.08395896409687646, -0.2515485929002174]
ours (h+hc+e): [-0.05601230589576848, -0.2236019346991094]
ours (h+d+a): [-0.023584103296993356, -0.03892546194470571]
ours (h+d+e): [-0.02372500974867356, -0.03927605327352016]
ours (h+o+a): [-0.07519206922026636, -0.06741264250697718]
ours (h+o+e): [-0.07484789586366422, -0.06704342162274564]
qpanda_5 (h+d): [-0.014263439466356814, -0.002288148948400603]
qpanda_5 (h+o): [-0.2372447294421276, 0.13505744146328122]
qpanda_alg: [-0.8567746 -1.6730434]
```

We even compare our method `ours` (configs) to the guessed implementation of QPanda with 5-qubits `qpanda_5` and the direct QAlg API `hhl_solve_linear_equations` (namely `qpanda_alg` here). As for the configs for our method, `r/h` indicates the transform method `reduce` or `hermitian`, `hc/d/o` indicates the the implementation for QPE unitary is `hard-coded`, `matrix_decompose` or `QOracle`, the final `a/e` indicates angles in the rotaion step is generally `approximated` or use exactly `eigval`.

The summarized conclusions are:

- QPanda's `matrix_decompose()` seems not reliable
- Our `hermitian` method behaves similiar like `qpanda_5`
- Our `reduce` method behaves similiar like `qpanda_alg`, but remeber, `qpanda_alg` requires much more qubits, while ours (`n`) need to inverse auxiliary matrix in classical process, which is cheaty 😞

references

- <https://arxiv.org/abs/0811.3171> (**root thesis**)
- <https://arxiv.org/abs/1110.2232>
- <https://arxiv.org/abs/1302.1210>
- <https://arxiv.org/abs/1805.10549>
- <https://arxiv.org/abs/1302.4310>
- <https://arxiv.org/abs/1302.1946>
- https://en.wikipedia.org/wiki/Quantum_algorithm_for_linear_systems_of_equations
- https://qiskit.org/textbook/ch-applications/hhl_tutorial.html (**highly recommended**)
- <https://zhuanlan.zhihu.com/p/164375189>
- <https://zhuanlan.zhihu.com/p/426811646>
- <https://www.qtumist.com/post/5212>
- <https://pyqpanda-toturial.readthedocs.io/zh/latest/HHL.html>
- https://en.wikipedia.org/wiki/Matrix_exponential
- https://en.wikipedia.org/wiki/Sylvester's_formula#special_case

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