

13. Utility-Scale Experiment II

Yukio Kawashima (July 12, 2024)

© IBM Corp. 2024

Approximate QPU time to run this experiment is 2 m 30 s.

Note that this notebook used texts, illustration, and codes in [a tutorial notebook \(https://github.com/qiskit-community/qiskit-algorithms/blob/main/docs/tutorials/13_trotterQRTE.ipynb\)](https://github.com/qiskit-community/qiskit-algorithms/blob/main/docs/tutorials/13_trotterQRTE.ipynb) for Qiskit Algorithms.

This notebook follows the methods and techniques of lesson 7. Our goal is to numerically solve the time-dependent Schrödinger equation. As discussed in lesson 7, Trotterization consists in the successive application of a quantum gate or gates, chosen to approximate the time evolution of a system for a time slice. We repeat that discussion here for convenience. Feel free to skip to the code cells below if you have recently reviewed lesson 7.

Following from the Schrödinger equation, the time evolution of a system initially in the state $|\psi(0)\rangle$ takes the form:

$$|\psi(t)\rangle = e^{-iHt}|\psi(0)\rangle,$$

where H is the time-independent Hamiltonian governing the system. We consider a Hamiltonian that can be written as a weighted sum of Pauli terms $H = \sum_j a_j P_j$, with P_j representing a tensor product of Pauli terms acting on n qubits. In particular, these Pauli terms might commute with one another, or they might not. Given a state at time $t = 0$, how do we obtain the system's state at a later time $|\psi(t)\rangle$ using a quantum computer? The exponential of an operator can be most easily understood through its Taylor series:

$$e^{-iHt} = 1 - iHt - \frac{1}{2}H^2t^2 + \dots$$

Some very basic exponentials, like e^{iZ} can be implemented easily on quantum computers using a compact set of quantum gates. Most Hamiltonians of interest will not have just a single term, but will instead have many terms. Note what happens if $H = H_1 + H_2$:

$$e^{-iHt} = 1 - i(H_1 + H_2)t - \frac{1}{2}(H_1 + H_2)^2t^2 + \dots$$

When H_1 and H_2 commute, we have the familiar case (which is also true for numbers, and variables a and b below):

$$e^{-i(a+b)t} = e^{-iat} e^{-ibt}$$

But when operators do not commute, terms cannot be rearranged in the Taylor series to simplify in this way. Thus, expressing complicated Hamiltonians in quantum gates is a challenge.

One solution is to consider very small time t , such that the first-order term in the Taylor expansion dominates. Under that assumption:

$$e^{-i(H_1+H_2)t} \approx 1 - i(H_1 + H_2)t \approx (1 - iH_1t)(1 - iH_2t) \approx e^{-iH_1t} e^{-iH_2t}$$

Of course, we may need to evolve our state for a longer time. That is accomplished by using many such small steps in time. This process is called Trotterization:

$$|\psi(t)\rangle \approx \left(\prod_j e^{-ia_j P_j t/r} \right)^r |\psi(0)\rangle,$$

Here t/r is the time slice (evolution step) that we are choosing. As a result, a gate to be applied r times is created. A smaller timestep leads to a more accurate approximation. However, this also leads to deeper circuits which, in practice, leads to more error accumulation (a non-negligible concern on near-term quantum devices).

Today, we will study the time evolution of the Ising model (https://en.wikipedia.org/wiki/Ising_model) on linear lattices of $N = 2$ and $N = 6$ sites. These lattices consist of an array of spins σ_i that interact only with their nearest neighbors. These spins can have two orientations: $\uparrow$ and $\downarrow$, which correspond to a magnetization of $+1$ and -1 respectively.

$$H = -J \sum_{i=0}^{N-2} Z_i Z_{i+1} - h \sum_{i=0}^{N-1} X_i,$$

where J describes the interaction energy, and h the magnitude of an external field (in the x-direction above, but we will modify this). Let us write this expression using Pauli matrices, and considering that the external field has an angle α with respect to the transversal direction,

$$H = -J \sum_{i=0}^{N-2} Z_i Z_{i+1} - h \sum_{i=0}^{N-1} (\sin \alpha Z_i + \cos \alpha X_i).$$

This Hamiltonian is useful in that it allows us to easily study the effects of an external field. In the computational basis, the system will be encoded as follows:

Quantum state	Spin representation
$ 0000\rangle$	$\uparrow\uparrow\uparrow\uparrow$
$ 1000\rangle$	$\downarrow\uparrow\uparrow\uparrow$
...	...
$ 1111\rangle$	$\downarrow\downarrow\downarrow\downarrow$

We will start investigating the time evolution of such a quantum system. More specifically, we will visualize the time-evolution of certain properties of the system like magnetization.

```
In [1]: 1 # Check the version of Qiskit
        2 import qiskit
        3 qiskit.__version__
```

```
Out[1]: '1.3.0'
```

```
In [2]: 1 # Import the qiskit library
        2 import math
        3 import numpy as np
        4 import scipy as sp
        5 import matplotlib.pyplot as plt
        6 from typing import Union, List
        7 import warnings
        8
        9 warnings.filterwarnings("ignore")
       10
       11 from qiskit import QuantumCircuit, QuantumRegister
       12 from qiskit.circuit.library import PauliEvolutionGate
       13 from qiskit.primitives import StatevectorEstimator
       14 from qiskit.quantum_info import Statevector, SparsePauliOp
       15 from qiskit.synthesis import (
       16     SuzukiTrotter,
       17     MatrixExponential,
       18     QDrift,
       19     ProductFormula,
       20     LieTrotter
       21 )
       22 from qiskit.transpiler.preset_passmanagers import generate_preset_pass_manager
       23
       24 from qiskit_aer import AerSimulator
       25 from qiskit_ibm_runtime import QiskitRuntimeService, Estimator
```

Code for defining the transverse-field Ising Hamiltonian

We here consider the 1-D transverse-field Ising model

First, we will create a function that takes in the system parameters N , J , and h , and returns our Hamiltonian as a `SparsePauliOp`. A `SparsePauliOp` (https://docs.quantum.ibm.com/api/qiskit/qiskit.quantum_info.SparsePauliOp) is a sparse representation of an operator in terms of weighted `Pauli` (https://docs.quantum.ibm.com/api/qiskit/qiskit.quantum_info.Pauli) terms.

Activity 1

Construct a function to build a transverse-field Ising Hamiltonian (see the equation above) with arguments of "the number of qubits", "J parameter", and "h parameter". Try this on your own using previous examples. Scroll down for the solution.

Solution:

```
In [4]: 1 def get_hamiltonian(nqubits, J, h):
        2
        3     # List of Hamiltonian terms as 3-tuples containing
        4     # (1) the Pauli string,
        5     # (2) the qubit indices corresponding to the Pauli string,
        6     # (3) the coefficient.
        7     ZZ_tuples = [("ZZ", [i, i + 1], -J) for i in range(0, nqubits - 1)]
        8     X_tuples = [("X", [i], -h) for i in range(0, nqubits)]
        9
       10     # We create the Hamiltonian as a SparsePauliOp, via the method
       11     # `from_sparse_list`, and multiply by the interaction term.
       12     hamiltonian = SparsePauliOp.from_sparse_list([*ZZ_tuples, *X_tuples], num_qubits=nqubits)
       13     return hamiltonian.simplify()
```

I. Solution using simulators

We will start investigating the time evolution of a quantum system, while keeping track of magnetization. We here compare the results of the Statevector and Matrix Product State simulators.

Define the Hamiltonian

The system that we now consider has a size of $N = 20$.

```
In [5]: 1 n_qubits = 20
        2 hamiltonian = get_hamiltonian(nqubits=n_qubits, J=1.0, h=-5.0)
        3 hamiltonian
```

[illegible]

Set the parameters of the time-evolution simulation

Here we will consider the Lie–Trotter (first order).

```
In [6]: 1 num_timesteps = 20
        2 evolution_time = 2.0
        3 dt = evolution_time / num_timesteps
        4 product_formula_lt = LieTrotter()
```

Prepare the quantum circuit (Initial state)

Create an initial state. We will start from the ground state, which is a ferromagnetic state (all up or all down). Here, we use an example of all ups (which is all '0').

```
In [7]: 1 initial_circuit = QuantumCircuit(n_qubits)
        2 initial_circuit.prepare_state('00000000000000000000')
        3 # Change reps and see the difference when you decompose the circuit
        4 initial_circuit.decompose(reps=1).draw("mpl")
```

Out[7]:

q_0 —

q_1 —

q_2 —

q_3 —

q_4 —

Prepare the quantum circuit 2 (Single circuit for time evolution)

We here construct a circuit for a single time step using Lie–Trotter.

The Lie product formula (first order) is implemented in the `LieTrotter` (<https://docs.quantum.ibm.com/api/qiskit/qiskit.synthesis.LieTrotter>) class. A first order formula consists of the approximation stated in the introduction, where the matrix exponential of a sum is approximated by a product of matrix exponentials:

$$e^{H_1+H_2} \approx e^{H_1} e^{H_2}$$

Let us count the operations for this circuit.

```

In [8]: 1 single_step_evolution_gates_lt = PauliEvolutionGate(
        2     hamiltonian, dt, synthesis=product_formula_lt
        3 )
        4 single_step_evolution_lt = QuantumCircuit(n_qubits)
        5 single_step_evolution_lt.append(single_step_evolution_gates_lt, single_step_evolution_lt.qubits)
        6
        7 print(
        8     f"""
        9 Trotter step with Lie-Trotter
       10 -----
       11 Depth: {single_step_evolution_lt.decompose(reps=3).depth()}
       12 Gate count: {len(single_step_evolution_lt.decompose(reps=3))}
       13 Nonlocal gate count: {single_step_evolution_lt.decompose(reps=3).num_nonlocal_gates()}
       14 Gate breakdown: {"", ".join([f"{k.upper()}: {v}" for k, v in single_step_evolution_lt.decompose(reps=3).
       15     """)
       16 )
       17 single_step_evolution_lt.decompose(reps=3).draw("mpl", fold=-1)

```

Trotter step with Lie-Trotter

Depth: 58

Gate count: 77

Nonlocal gate count: 38

Gate breakdown: CX: 38, U3: 20, U1: 19

Global Phase: 1.9220566666666666



Set the operators to be measured

Let us define a *magnetization operator* $\sum_i Z_i/N$.

In [9]:

```
1 magnetization= SparsePauliOp.from_sparse_list(
2     [("Z", [i], 1.0) for i in range(0, n_qubits)], num_qubits=n_qubits
3 ) / n_qubits
4 print('magnetization : ', magnetization)
```

```
magnetization : SparsePauliOp(['IIIIIIIIIIIIIIIIIIZ', 'IIIIIIIIIIIIIIIIIZI', 'IIIIIIIIIIIIIIIIIZII', 'I  
IIIIIIIIIIIIIIIIIZIII', 'IIIIIIIIIIIIIIIIIZIII', 'IIIIIIIIIIIIIIIIIZIIII', 'IIIIIIIIIIIIIIIIIZIIII', 'IIIIIIIIII  
IZIIIIII', 'IIIIIIIIIIIZIIIIII', 'IIIIIIIIIIIZIIIIIIII', 'IIIIIIIIIZIIIIIIIIII', 'IIIIIIIIIZIIIIIIIIII',  
, 'IIIIIIIIIZIIIIIIIIII', 'IIIIIIIZIIIIIIIIIIII', 'IIIIIZIIIIIIIIIIIIII', 'IIIIIZIIIIIIIIIIIIII', 'IIIZIIII  
IIIIIIIIIIIIII', 'IIIZIIIIIIIIIIIIIIII', 'IZIIIIIIIIIIIIIIIIII', 'ZIIIIIIIIIIIIIIIIIIII'],  
      coeffs=[0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j,  
      0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j,  
      0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j, 0.05+0.j])
```

Perform time-evolution simulation

We will monitor the magnetization (expectation value of the magnetization operator). We will use Statevector and MPS simulators and compare the results.

In [10]:

```
1 # Step 1. Map the problem
2 # Initiate the circuit
3 evolved_state = QuantumCircuit(initial_circuit.num_qubits)
4 # Start from the initial spin configuration
5 evolved_state.append(initial_circuit, evolved_state.qubits)
6
7 # Define backend (simulator)
8 # MPS
9 backend_mps = AerSimulator(method='matrix_product_state')
10 # Statevector
11 backend_sv = AerSimulator(method='statevector')
12
13 # Set Runtime Estimator
14 # MPS
15 estimator_mps = Estimator(mode=backend_mps)
16 # Statevector
17 estimator_sv = Estimator(mode=backend_sv)
18
19 # Step 2. Optimize
20 # Set pass manager
21 # MPS
22 pm_mps = generate_preset_pass_manager(optimization_level=3, backend=backend_mps)
23 # Statevector
24 pm_sv = generate_preset_pass_manager(optimization_level=3, backend=backend_sv)
25
26 # Transpile initial circuit
27 # MPS
28 evolved_state_mps = pm_mps.run(evolved_state)
29 # Statevector
30 evolved_state_sv = pm_sv.run(evolved_state)
31
32 # Apply layout to the operator
33 # MPS
34 magnetization_mps = magnetization.apply_layout(evolved_state_mps.layout)
35 # Statevector
36 magnetization_sv = magnetization.apply_layout(evolved_state_sv.layout)
37
38 mag_mps_list = []
39 mag_sv_list = []
40
```

```

41 # Step 3. Run the circuit
42 # Estimate expectation values for t=0.0: MPS
43 job = estimator_mps.run([(evolved_state_mps, [magnetization_mps])])
44 # Get estimated expectation values: MPS
45 evs = job.result()[0].data.evs
46 # Collect data: MPS
47 mag_mps_list.append(evs[0])
48
49 # Estimate expectation values for t=0.0: Statevector
50 job = estimator_sv.run([(evolved_state_sv, [magnetization_sv])])
51 # Get estimated expectation values: Statevector
52 evs = job.result()[0].data.evs
53 # Collect data: Statevector
54 mag_sv_list.append(evs[0])
55
56 # Start time evolution
57 for n in range(num_timesteps):
58     # Step 1. Map the problem
59     # Expand the circuit to describe delta-t
60     evolved_state.append(single_step_evolution_lt, evolved_state.qubits)
61     # Step 2. Optimize
62     # Transpile the circuit: MPS
63     evolved_state_mps = pm_mps.run(evolved_state)
64     # Apply the physical layout of the qubits to the operator: MPS
65     magnetization_mps = magnetization.apply_layout(evolved_state_mps.layout)
66     # Step 3. Run the circuit
67     # Estimate expectation values at delta-t: MPS
68     job = estimator_mps.run([(evolved_state_mps, [magnetization_mps])])
69     # Get estimated expectation values: MPS
70     evs = job.result()[0].data.evs
71     # Collect data: MPS
72     mag_mps_list.append(evs[0])
73
74     # Step 2. Optimize
75     # Transpile the circuit: Statevector
76     evolved_state_sv = pm_sv.run(evolved_state)
77     # Apply the physical layout of the qubits to the operator: Statevector
78     magnetization_sv = magnetization.apply_layout(evolved_state_sv.layout)
79     # Step 3. Run the circuit
80     # Estimate expectation values at delta-t: Statevector
81     job = estimator_sv.run([(evolved_state_sv, [magnetization_sv])])

```

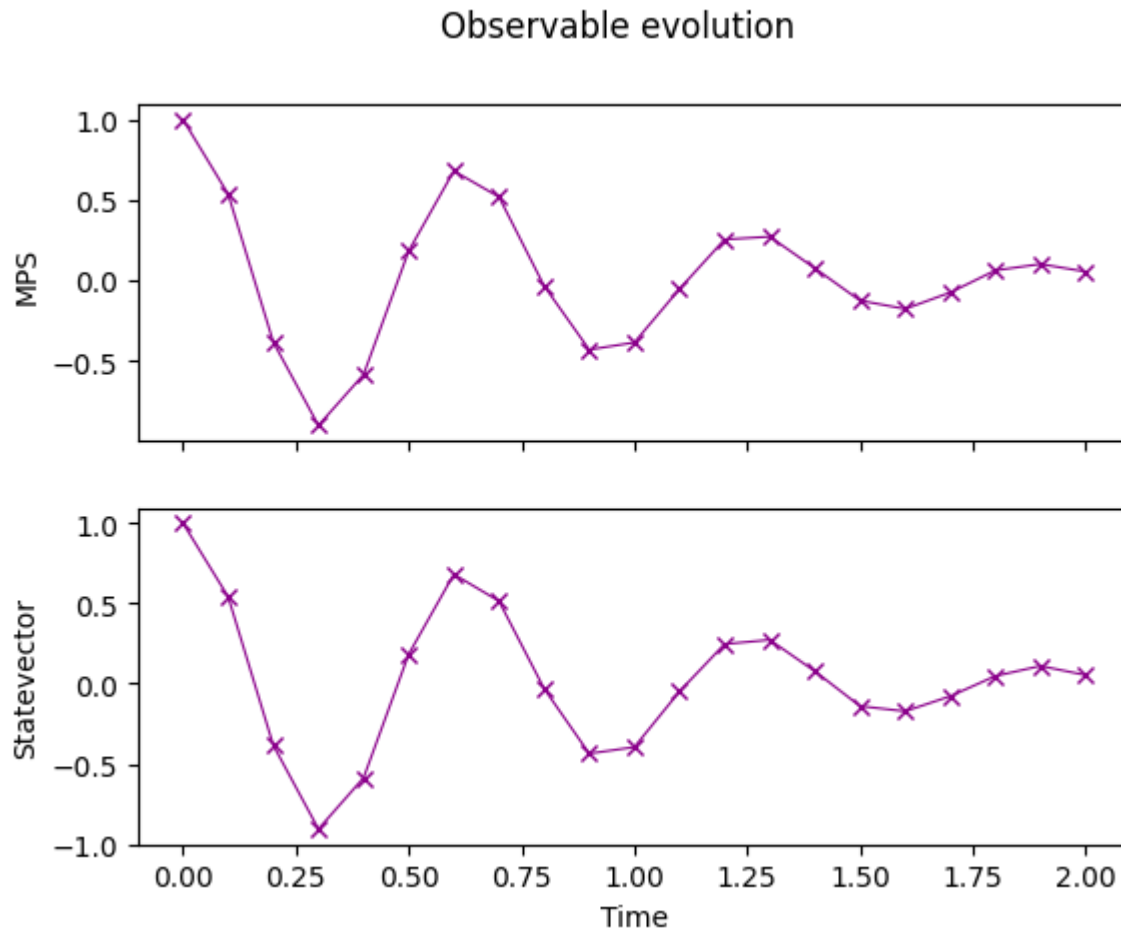
```
82     # Get estimated expectation values: Statevector
83     evs = job.result()[0].data.evs
84     # Collect data: Statevector
85     mag_sv_list.append(evs[0])
86
87     # Transform the list of expectation values (at each time step) to arrays
88     mag_mps_array = np.array(mag_mps_list)
89     mag_sv_array = np.array(mag_sv_list)
```

Plot the time evolution of the observables

We plot the expectation values we measured against time. Confirm that the results from statevector and matrix product space simulators agree.

```
In [11]: 1 import matplotlib.pyplot as plt
          2
          3 # Step 4. Postprocessing
          4 fig, axes = plt.subplots(2, sharex=True)
          5 times = np.linspace(0, evolution_time, num_timesteps + 1) # includes initial state
          6 axes[0].plot(
          7     times, mag_mps_array, label="MPS", marker="x", c="darkmagenta", ls="-", lw=0.8
          8 )
          9 axes[1].plot(
         10     times, mag_sv_array , label="SV", marker="x", c="darkmagenta", ls="-", lw=0.8
         11 )
         12
         13 axes[0].set_ylabel("MPS")
         14 axes[1].set_ylabel("Statevector")
         15 axes[1].set_xlabel("Time")
         16 fig.suptitle("Observable evolution")
```

```
Out[11]: Text(0.5, 0.98, 'Observable evolution')
```



II. Solution using real quantum computers

We will start investigating the time evolution of a quantum system, while keeping track of properties. We here compare the results of the Matrix Product State simulator and the actual quantum device.

Activity 2

Define the Hamiltonian

The system that we now consider has a size of $N = 70$. Note that the other conditions are the same from the 20-qubit problem. Try this on your own; scroll down for the solution.

Solution:

```
In [12]: 1 # Set the number of qubits
          2 n_qubits2 = 70
          3 # Construct the Hamiltonian by calling the function you made in Activity 1
          4 hamiltonian2 = get_hamiltonian(nqubits=n_qubits2, J=1.0, h=-5.0)
          5 hamiltonian2
```

[illegible]

Activity 3

Create an initial state. We will start from the ground state, which is a ferromagnetic state (all up or all down). Here, we use an example of all ups (which is all '0'). Try this on your own; scroll down for the solution.

Solution:

```
In [13]: 1 # Initiate the (quantum)circuit
2 initial_circuit2 = QuantumCircuit(n_qubits2)
3 # Use QuantumCircuit.prepare_state() to define the initial state
4 initial_circuit2.prepare_state('0000000000000000000000000000000000000000000000000000000000000000')
5 # Change reps and see the difference when you decompose the circuit
6 initial_circuit2.decompose(reps=1).draw("mpl")
```

Out[13]:

 $q_0 \text{ —}$ $q_1 \text{ —}$ q_2 — $q_3 \text{ —}$ q_4 —

Activity 4

Prepare the quantum circuit 2 (Single circuit for time evolution) for the 70-qubit problem

We here construct a circuit for a single time step using Lie–Trotter.

Exactly as in the 20-qubit case, the Lie product formula (first order) is implemented in the `LieTrotter` (<https://docs.quantum.ibm.com/api/qiskit/qiskit.synthesis.LieTrotter>) class. Again the first order formula consists of the approximation stated above:

$$e^{H_1+H_2} \approx e^{H_1} e^{H_2}$$

Try this yourself, building from the example of the 20-qubit case. As before, count the operations for this circuit.

Solution:

```

In [14]: 1 # Construct the gates using PauliEvolutionGate()
          2 single_step_evolution_gates_lt2 = PauliEvolutionGate(
          3     hamiltonian2, dt, synthesis=LieTrotter()
          4 )
          5 # Initiate the quantum circuit
          6 single_step_evolution_lt2 = QuantumCircuit(n_qubits2)
          7 # Append the gates defined above
          8 single_step_evolution_lt2.append(single_step_evolution_gates_lt2, single_step_evolution_lt2.qubits)
          9
         10 print(
         11     f"""
         12 Trotter step with Lie-Trotter
         13 -----
         14 Depth: {single_step_evolution_lt2.decompose(reps=3).depth()}
         15 Gate count: {len(single_step_evolution_lt2.decompose(reps=3))}
         16 Nonlocal gate count: {single_step_evolution_lt2.decompose(reps=3).num_nonlocal_gates()}
         17 Gate breakdown: {"", ".join([f"{k.upper()}: {v}" for k, v in single_step_evolution_lt2.decompose(reps=3)
         18     """)
         19 )
         20 single_step_evolution_lt2.decompose(reps=3).draw("mpl", fold=-1)

```

Trotter step with Lie-Trotter

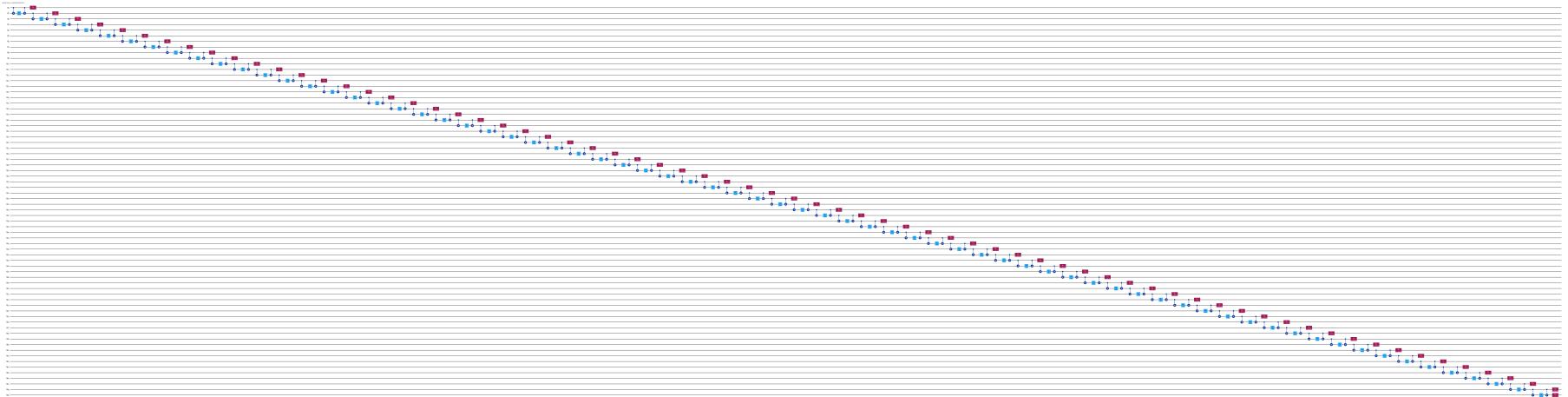
Depth: 208

Gate count: 277

Nonlocal gate count: 138

Gate breakdown: CX: 138, U3: 70, U1: 69

Out[14]:



Activity 5

Set the operators to be measured

We define a *magnetization operator* exactly analogous to the one from the 20-qubit case: $\sum_i Z_i/N$. Try this yourself by modifying the 20-qubit solution.

Solution:

```
In [15]: 1 # Define the magnetization operator in SparsePauliOp
          2 magnetization2= SparsePauliOp.from_sparse_list(
          3     [("Z", [i], 1.0) for i in range(0, n_qubits2)], num_qubits=n_qubits2
          4 ) / n_qubits2
          5 print('magnetization : ', magnetization2)
```

[illegible]

necessary to fit this new calculation.

Solution:

In [16]:

```
1 # Step 1. Map the problem
2 # Initiate the circuit
3 evolved_state2 = QuantumCircuit(initial_circuit2.num_qubits)
4 # Start from the initial spin configuration
5 evolved_state2.append(initial_circuit2, evolved_state2.qubits)
6 # Define backend (MPs simulator)
7 backend_mps2 = AerSimulator(method='matrix_product_state')
8 # Initiate Runtime Estimator
9 estimator_mps2 = Estimator(mode=backend_mps2)
10 # Step 2. Optimize
11 # Initiate pass manager
12 pm_mps2 = generate_preset_pass_manager(optimization_level=3, backend=backend_mps2)
13 # Transpile
14 evolved_state_mps2 = pm_mps2.run(evolved_state2)
15 # Apply qubit layout to the observable to measure
16 magnetization_mps2 = magnetization2.apply_layout(evolved_state_mps2.layout)
17 # Initiate list
18 mag_mps_list2 = []
19 # Step 3. Run the circuit
20 # Estimate expectation values for t=0.0
21 job = estimator_mps2.run([(evolved_state_mps2, [magnetization_mps2])])
22 # Get estimated expectation values
23 evs = job.result()[0].data.evs
24 # Append to list
25 mag_mps_list2.append(evs[0])
26
27 # Start time evolution
28 for n in range(num_timesteps):
29     # Step 1. Map the problem
30     # Expand the circuit to describe delta-t
31     evolved_state2.append(single_step_evolution_lt2, evolved_state2.qubits)
32     # Step 2. Optimize
33     # Transpile the circuit
34     evolved_state_mps2 = pm_mps2.run(evolved_state2)
35     # Apply the physical layout of the qubits to the operator
36     magnetization_mps2 = magnetization2.apply_layout(evolved_state_mps2.layout)
37     # Step 3. Run the circuit
38     # Estimate expectation values at delta-t
39     job = estimator_mps2.run([(evolved_state_mps2, [magnetization_mps2])])
40     # Get estimated expectation values
```

```
41     evs = job.result()[0].data.evs
42     # Append to list
43     mag_mps_list2.append(evs[0])
44 # Transform the list of expectation values (at each time step) to arrays
45 mag_mps_array2 = np.array(mag_mps_list2)
```

Solution using a real quantum computer

As in all previous lessons, we will implement the Qiskit patterns framework. The lesson up to this point has been focused on creating the correct quantum circuits to describe our problem. This is effectively Step 1.

Step 2: Optimize for target hardware

We start by defining the target backend.

```
In [16]: 1 service = QiskitRuntimeService(channel="ibm_quantum")
          2 backend = service.least_busy(operational=True, simulator=False)
          3 backend.name
```

```
Out[16]: 'ibm_sherbrooke'
```

We transpile the circuits and gather them in a list. This may take a few minutes.

```
In [17]: 1 pm_hw = generate_preset_pass_manager(optimization_level=3, backend=backend)
2 circuit_isa = []
3 # Step 1. Map the problem
4 evolved_state_hw = QuantumCircuit(initial_circuit2.num_qubits)
5 evolved_state_hw.append(initial_circuit2, evolved_state_hw.qubits)
6 # Step 2. Optimize
7 circuit_isa.append(pm_hw.run(evolved_state_hw))
8
9 for n in range(num_timesteps):
10     # Step 1. Map the problem
11     evolved_state_hw.append(single_step_evolution_lt2, evolved_state_hw.qubits)
12     # Step 2. Optimize
13     circuit_isa.append(pm_hw.run(evolved_state_hw))
```

Step 3: Execute on target hardware

We will define the Runtime Estimator and construct the list of PUBs. We must also apply the layout to the operators to be measured.

```
In [18]: 1 # Step 2. Optimize
2 estimator_hw = Estimator(mode=backend)
3 pub_list=[]
4 for circuit in circuit_isa:
5     temp = (circuit, magnetization2.apply_layout(circuit.layout))
6     pub_list.append(temp)
```

We are now ready to run the job.

```
In [19]: 1 job = estimator_hw.run(pub_list)
2 print(job.job_id())
```

cvv5jch7cb40008e5bw0

Step 4: Post-process results

We will first get the results.

```
In [20]: 1 pub_result = job.result()
```

Now we must extract the expectation values from these results.

```
In [21]: 1 mag_hw_list = []  
2 for res in pub_result:  
3     evs = res.data.evs  
4     mag_hw_list.append(evs)
```

We will use this for comparison below. First, let us see if we can optimize our circuits even further.

Solution using a real quantum computer II

Let us return to Qiskit patterns step 1, and see if we can reduce the depth of our circuit.

Step 1. Map the problem to quantum circuits and operators

Activity 7

Construct a time-evolution circuit. Use your knowledge from previous lessons to try to reduce the depth of the circuit.

Solution:

In [22]:

```
1 # Define J
2 J=1.0
3 # Define h
4 h=-5.0
5 # Create instruction for rotation around ZZ:
6 # Initiate the circuit (use 2 qubits)
7 Rzz_circ = QuantumCircuit(2)
8 # Add Rzz gate (do not forget to multiply the angle by 2.0)
9 Rzz_circ.rzz(-J*dt*2.0, 0, 1)
10 # Transform the QuantumCircuit to instruction (QuantumCircuit.to_instruction())
11 Rzz_instr = Rzz_circ.to_instruction(label="RZZ")
12
13 # Create instruction for rotation around X:
14 # Initiate the circuit (use 1 qubit)
15 Rx_circ = QuantumCircuit(1)
16 # Add Rx gate (do not forget to multiply the angle by 2.0)
17 Rx_circ.rx(-h*dt*2.0, 0)
18 # Transform the QuantumCircuit to instruction (QuantumCircuit.to_instruction())
19 Rx_instr = Rx_circ.to_instruction(label="RX")
20
21 # Define the interaction list
22 interaction_list = [
23     [[i, i + 1] for i in range(0, n_qubits2 - 1, 2)],
24     [[i, i + 1] for i in range(1, n_qubits2 - 1, 2)],
25 ] # linear chain
26
27 # Define the registers
28 qr = QuantumRegister(n_qubits2)
29 # Initiate the circuit
30 single_step_evolution_sh = QuantumCircuit(qr)
31 # Construct the Rzz gates
32 for i, color in enumerate(interaction_list):
33     for interaction in color:
34         single_step_evolution_sh.append(Rzz_instr, interaction)
35
36 # Construct the Rx gates
37 for i in range(0, n_qubits2):
38     single_step_evolution_sh.append(Rx_instr, [i])
39
40 print(
```



```
In [23]: 1 pm_hw2 = generate_preset_pass_manager(backend=backend, optimization_level=3)
2 circuit_isa2 = []
3 # Step 1. Map the problem
4 evolved_state_hw2 = QuantumCircuit(initial_circuit2.num_qubits)
5 evolved_state_hw2.append(initial_circuit2, evolved_state_hw2.qubits)
6 # Step 2. Optimize
7 circuit_isa2.append(pm_hw2.run(evolved_state_hw2))
8 for n in range(num_timesteps):
9     # Step 1. Map the problem
10     evolved_state_hw2.append(single_step_evolution_sh, evolved_state_hw2.qubits)
11     # Step 2. Optimize
12     circuit_isa2.append(pm_hw2.run(evolved_state_hw2))
```

Define the Runtime Estimator and construct the list of PUBs.

```
In [24]: 1 estimator_hw2 = Estimator(mode=backend)
2 pub_list2=[]
3 for circuit in circuit_isa2:
4     temp = (circuit, magnetization2.apply_layout(circuit.layout))
5     pub_list2.append(temp)
```

Step 3. Execute on target hardware

Run the job.

```
In [25]: 1 job2 = estimator_hw2.run(pub_list2)
2 print(job2.job_id())
```

cvv5nny5sat0008hwtg

Get the results.

```
In [26]: 1 pub_result2 = job2.result()
```

Step 4. Postprocessing

Extract the expectation values from the results.

```
In [27]: 1 mag_hw_list2 = []  
        2 for res in pub_result2:  
        3     evs = res.data.evs  
        4     mag_hw_list2.append(evs)
```

Transform the list into numpy arrays for plotting.

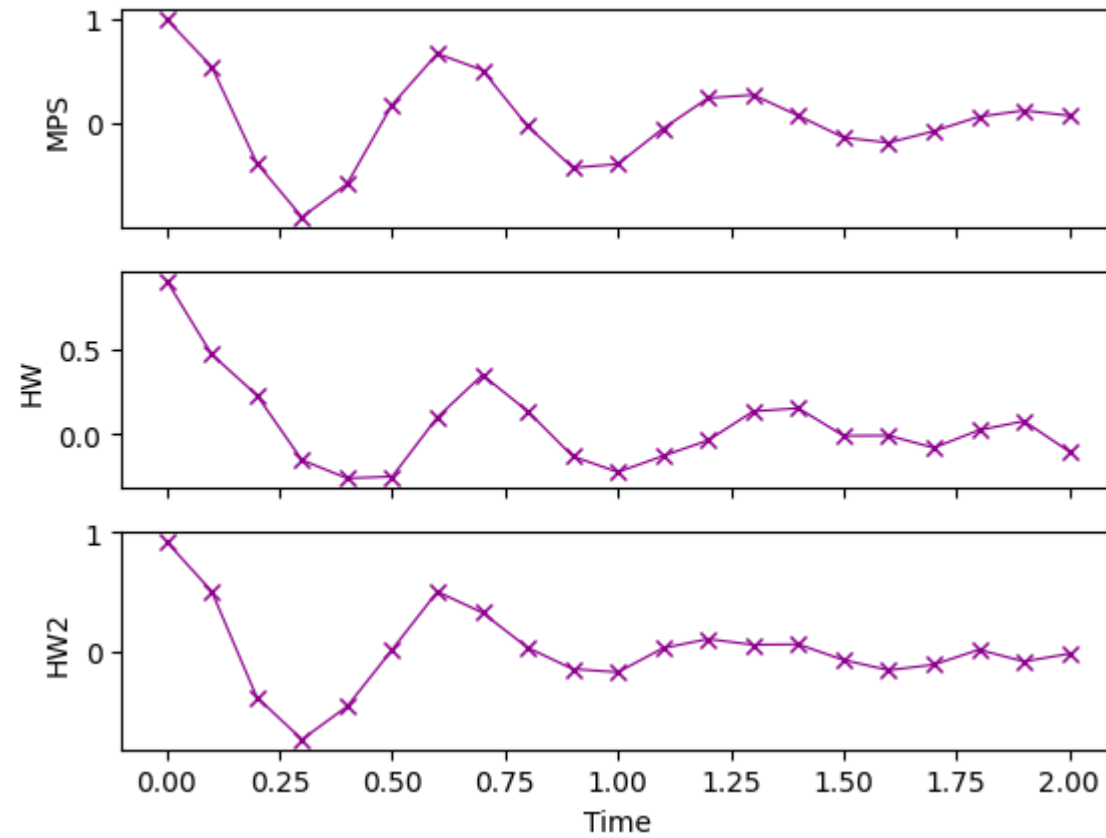
```
In [28]: 1 mag_hw_array = np.array(mag_hw_list)  
        2 mag_hw_array2 = np.array(mag_hw_list2)
```

Now let us plot the results and compare the hardware (default and shallow circuit) results with the MPS simulator. How does the error in the real hardware influence the results?

```
In [29]: 1 fig, axes = plt.subplots(3, sharex=True)
2 times = np.linspace(0, evolution_time, num_timesteps + 1) # includes initial state
3 axes[0].plot(
4     times, mag_mps_array2, label="MPS", marker="x", c="darkmagenta", ls="-", lw=0.8
5 )
6 axes[1].plot(
7     times, mag_hw_array , label="HW", marker="x", c="darkmagenta", ls="-", lw=0.8
8 )
9 axes[2].plot(
10    times, mag_hw_array2 , label="HW2", marker="x", c="darkmagenta", ls="-", lw=0.8
11 )
12 axes[0].set_ylabel("MPS")
13 axes[1].set_ylabel("HW")
14 axes[2].set_ylabel("HW2")
15 axes[2].set_xlabel("Time")
16 fig.suptitle("Observable evolution")
```

```
Out[29]: Text(0.5, 0.98, 'Observable evolution')
```

Observable evolution



Congratulations! You have moved one step further in your utility-scale quantum journey. There is only one lesson left!