Travelling Salesman Problem via Quantum Annealing

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What is TSP?

Objective: find the shortest possible path allowing a salesman to visit given cities exactly once before returning to original city.

NP-Hard problem



Classical algorithms struggle to find optimal solutions efficiently, opening the potential of a quantum approach.

Applications of TSP

- Delivery Routing
- Warehouse Picking
- Machine Scheduling
- Airline Scheduling
- Railroad Scheduling
- Network Design
- Genome Sequencing
- Public Transit
- Crop Spraying











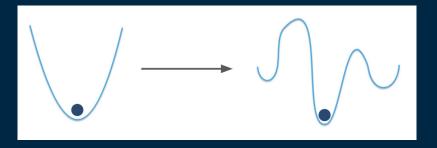




Quantum Annealing

- Annealing: optimize solutions to problems by quickly searching a space, and finding the global minimum, which is the solution.
- Quantum annealing focuses on solving optimization problems, and generally not based on quantum circuits.
- We will be using adiabatic quantum computing:
 - Start with simple optimized solution.
 - Space is explored and changes to a more complicated one.
 - We can still guarantee that it will remain the minimum.





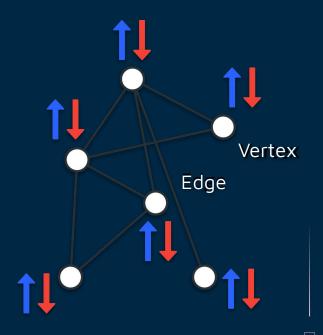
Hamiltonian



- We can model quantum annealing with the Hamiltonian, known as the ground-state problem.
 - Hamiltonian gives the total energy of a system.
 - We want to find the state of qubits that give lowest energy of a system.
- **Energy**: What we're calculating.
- Initial: Lowest energy state is where qubit is in superposition of 0 and 1.
- **Final**: As you anneal, problem Hamiltonian is introduced.
 - Eventually, as it reaches the end of the anneal, the Energy becomes solely the final.
- You've stayed in minimum energy state the entire time!

Plan

- 1. Mapping TSP to Ising Model
- 2. Formulate Ising Model into QUBO
- 3. Apply Quantum Annealing
- 4. Validate Results





```
from scripts import utilities
from scripts import plots
import matplotlib.pyplot as plt
# cities = utilities.create_cities(3)
cities = np.array([[0, 4],[0, 0],[3, 0]])
distance_matrix = utilities.get_distance_matrix(cities)
plots.plot_cities(cities)
plt.show()
                 1.0
                       1.5
  0.0
         0.5
                               2.0
                                      2.5
```

```
distance_matrix = utilities.get_distance_matrix(cities)
print(distance_matrix)
number_of_cities = len(cities)

[[0. 4. 5.]
[4. 0. 3.]
[5. 3. 0.]]
```

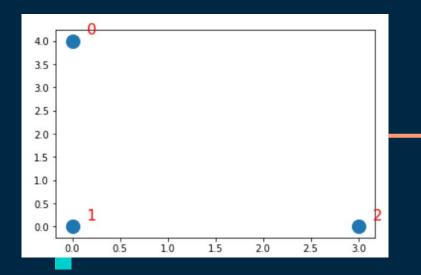
The last time we learned two useful equations for MaxCut which will guide us now.

One for the classical cost function:

$$C_{total} = \sum C_{ij} = \sum \frac{1}{2} w_{ij} (1 - z_i z_j),$$

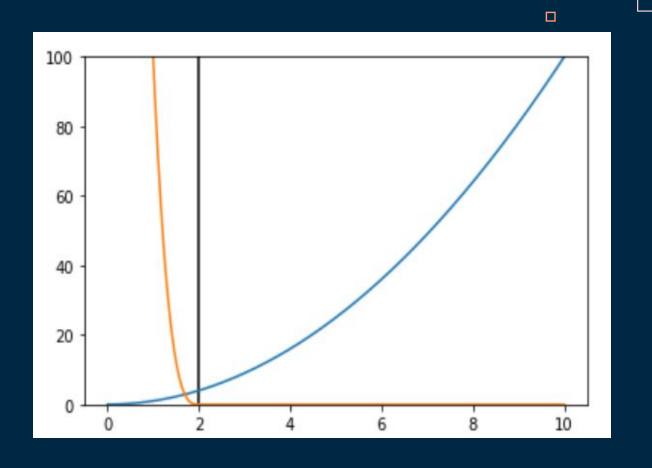
And one showing how to construct the quantum cost operator:

$$H_{cost} = \sum rac{1}{2} w_{ij} (\mathbb{1} - \sigma_i^z \sigma_j^z)$$



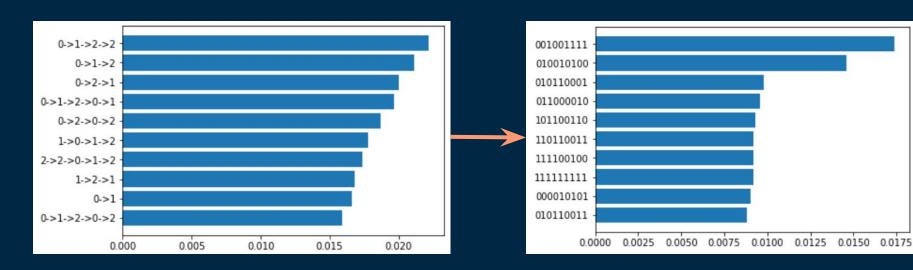
City 0 to 1 at t = 0 costs -2.0 Qubits: 0 4
City 0 to 1 at t = 1 costs -2.0 Qubits: 3 7
City 0 to 2 at t = 0 costs -2.5 Qubits: 0 5
City 0 to 2 at t = 1 costs -2.5 Qubits: 3 8
City 1 to 2 at t = 0 costs -1.5 Qubits: 1 5
City 1 to 2 at t = 1 costs -1.5 Qubits: 4 8

```
for single_cost_operator in cost_operators:
      print(single cost operator)
(-2+0j)*I + (2-0j)*Z0*Z4
(-2+0j)*I + (2-0j)*Z3*Z7
(-2.5+0j)*I + (2.5-0j)*Z0*Z5
(-2.5+0j)*I + (2.5-0j)*Z3*Z8
(-1.5+0j)*I + (1.5-0j)*Z1*Z5
(-1.5+0j)*I + (1.5-0j)*Z4*Z8
```



Classical TSP

Quantum TSP





References

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- https://github.com/mstechly/quantum_tsp_tutorials/tree/master