



Variational Quantum Classifier for Heart Disease Prediction

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Problem

Explore the implementation of a framework to predict heart disease using a Variational Quantum Classifier (VQC).

Problem

Binary classification of patient data to predict the presence of heart disease

Variational Quantum Classifier (VQC)

Evolutionary computation ➡ Quantum Circuit Parameter Optimization

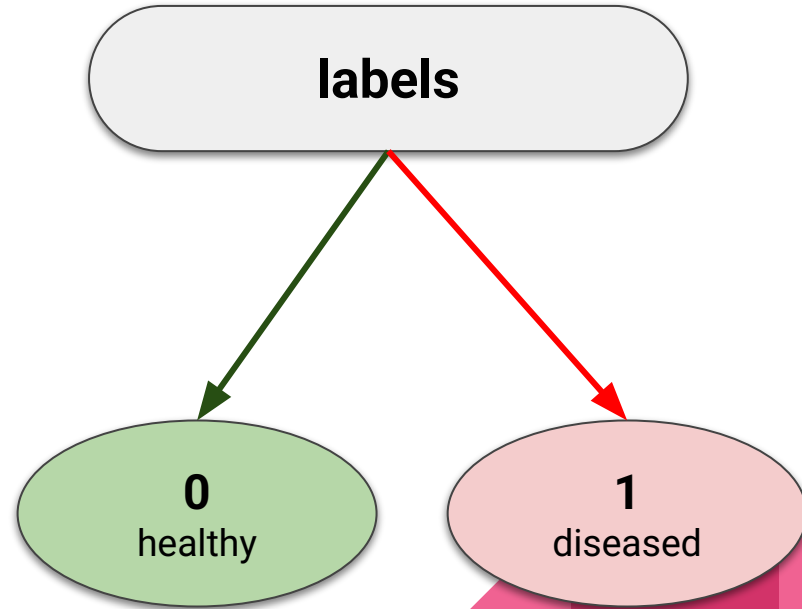
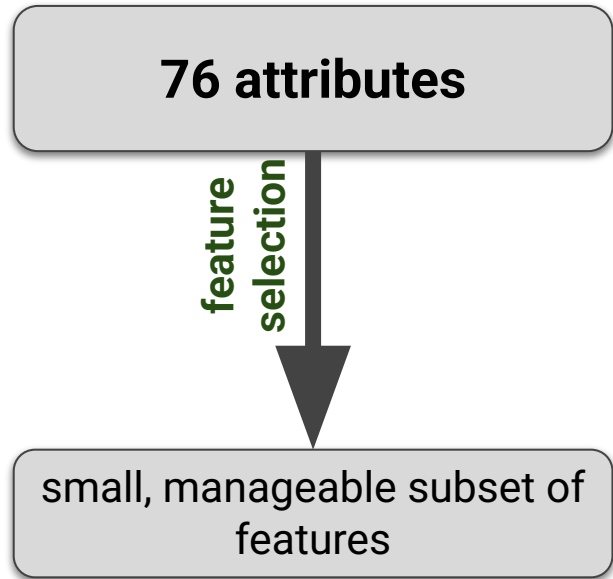


Pipeline

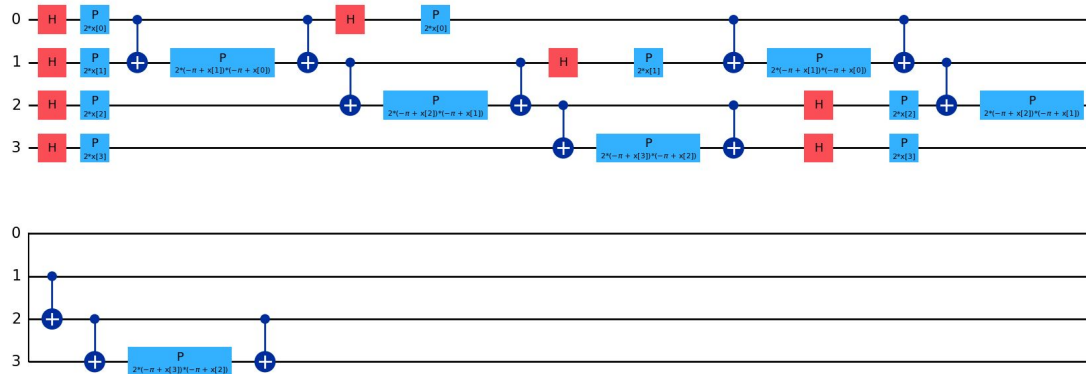
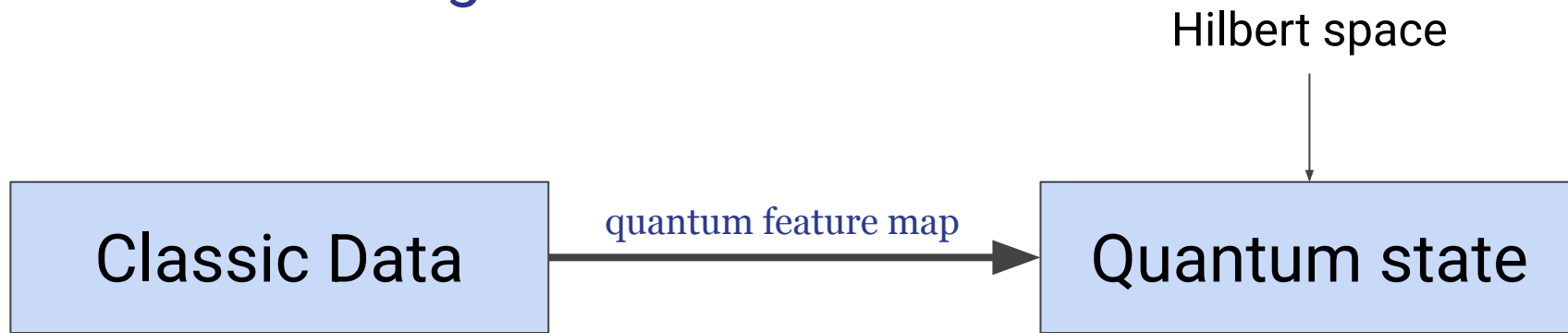
- Prerequisites Setup
- Defined Constants
- Data Preparation
- Quantum Circuit Preparation
- Utility Function
- Classification and Cost Evaluation
- Execution and Optimization
- Result Visualization



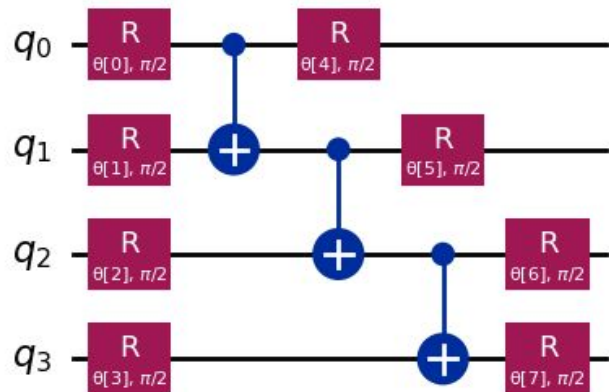
Database - UCI Heart Disease Dataset



Data embedding



Quantum Circuit Preparation



```
ansatz = real_amplitudes(  
    num_qubits = QUBIT_COUNT, # Number of qubits = number of features  
    reps = 1,                  # One repetition layer of rotations + entanglement  
    entanglement = 'linear'   # Linear entanglement between qubits  
)
```

Quantum Circuit Composition \Rightarrow data-encoding feature map + the parameterized ansatz circuit

Quantum Circuit Utility Functions

- **Parameter Dictionary Creation for Quantum Circuit**
- **Label Assignment Based on Bit String Parity**
- **Probability Calculation from Quantum Measurement Counts**



Classification and Cost Evaluation

Processing Details

- For each input feature vector:
 - Binds feature data and ansatz parameters to the quantum circuit.
 - Adds measurement operations to read out qubit states.
 - Transpiles/prepares the circuit for execution.
- Runs all circuits in batch on the quantum sampler.
- Converts measurement results into class probabilities using parity-based labeling.

Output

Returns a list of dictionaries, each containing class labels and their associated probabilities for the corresponding input feature vector.

```
def classify(x_list: list, params: list, sampler: any, pm: any) -> list:
    qc_list = []
    for x in x_list:
        # Bind input features and ansatz parameters to the circuit
        classifier = circuit.assign_parameters(get_data_dict(params, x))
        # Add measurement operations on all qubits
        classifier.measure_all()
        # Transpile or prepare the circuit for the backend
        transpiled_circuit = pm.run(classifier)
        qc_list.append(transpiled_circuit)
    # Execute all circuits on the simulator or quantum backend
    results = sampler.run(qc_list, shots=SHOT_COUNT).result()
    probs = []
    for qc in results:
        # Extract counts of measurement outcomes
        counts = qc.data.meas.get_counts()
        # Convert counts to probabilities for each class label
        prob = return_probabilities(counts)
        probs.append(prob)
    return probs
```

Cost Functions

Binary Cross-Entropy Cost

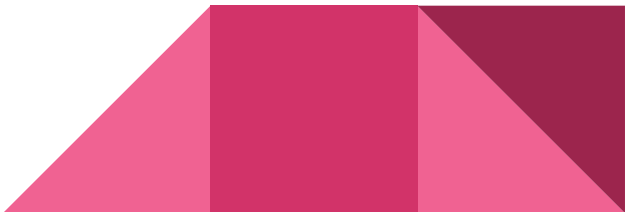
Calculates the *Binary Cross-Entropy* (BCE) loss for a predicted probability corresponding to the expected class label.

Cost Function for Quantum Circuit Training

Calculates the *average loss over the dataset* by comparing predicted probabilities against expected labels using Binary Cross-Entropy.

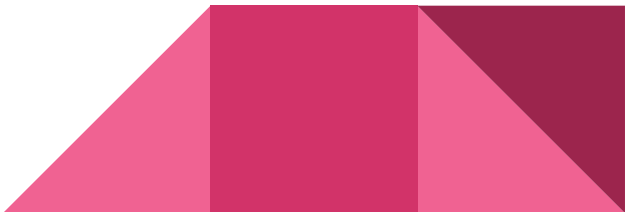
We will define an **Objective Function** – a cost function that evaluates how well, for a given parameter set, the training data is classified.

Quantum Circuit Parameter Optimization

- **CMA-ES** (Covariance Matrix Adaptation Evolution Strategy):
 - Evolutionary algorithm suitable for noisy or non-convex problems
 - Handles parameter noise using `cma.NoiseHandler`
 - Controlled by `CMA_ITER_COUNT`
 - **COBYLA** (Constrained Optimization BY Linear Approximations):
 - Gradient-free optimizer based on linear approximations
 - Ideal for small parameter spaces and quick iterations
 - Controlled by `COBYLA_ITER_COUNT`
- 

Quantum Circuit Parameter Optimization

Processing Details

1. **Initialize Parameters** Randomly initialized in the range $[0, 2\pi]$ to match typical rotation gate requirements for angle encoding.
 2. **Define Objective Function** The cost function evaluates how well a given parameter set classifies training data.
 3. **Run Optimization** Depending on the flag, either CMA-ES or COBYLA minimizes the cost over several iterations.
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Results and Validation


accuracy in simulations without noise

Cobyla	CMA-ES	SVM non-quantum method
86%	75%	81.81%


accuracy in simulations with noise

Cobyla	CMA-ES	SVM non-quantum method
70% – 85% more frequent towards 85%	74% when using a NoiseHandler, closer to ~83%	81.81%

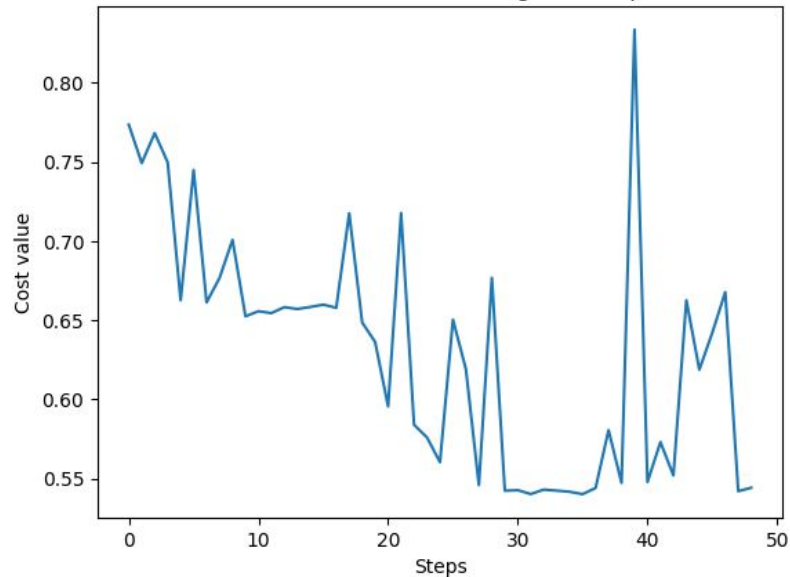
Running on QPU

- Training Iterations:
 - Completed 49 out of 70 planned iterations before the sessions were continuously marked as “Pending” on the IBM Quantum platform.
 - Backends & Region:
 - Used `ibm_fez` in the US-East region.
 - Also attempted to use `ibm_kingston` (least busy at the time), but sessions were pending and did not execute.
 - Runtime & Queueing:
 - Total runtime: ~7–8 hours.
 - Each iteration took approximately 2m 20s to 2m 50s of actual QPU time.
 - Additional time lost due to queue delays — queues ranged from 20 to 35 users.
- 

Running on QPU

- **Training Performance:**
 - Binary Cross Entropy (BCE) cost plateaued around 0.54 and did not drop lower during training.
 - **Accuracy Evaluation:**
 - Achieved an accuracy of $\sim 74\%$.
 - Standard deviation = 0.0000, with a 95% confidence interval of [0.7386, 0.7386].
 - The lack of variation may be due to the use of a fixed random seed (seed = 42) during testing.
 - **Comparison with Local Simulations:**
 - Accuracy on local (noisy) simulators varied widely: 70%–85%, depending on the run.
 - While the QPU run scored slightly below some simulated runs, it is still promising, especially given that the cost function typically stabilizes around iteration 65–70 — beyond the 49 reached here.
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COBYLA BCE Cost value against steps

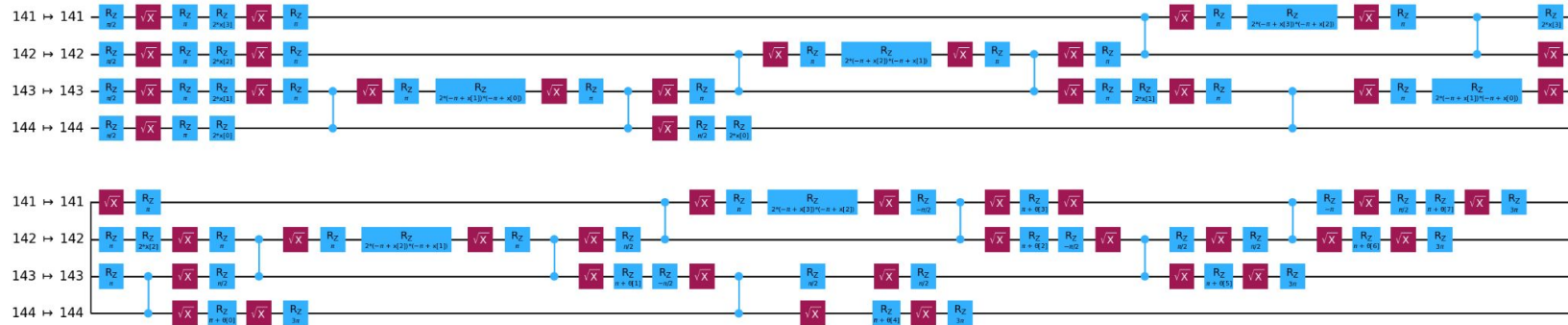


Running model testing over 30 iterations...

```

Iteration 1/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 2/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 3/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 4/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 5/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 6/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 7/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 8/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 9/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 10/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 11/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 12/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 13/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 14/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 15/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 16/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 17/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 18/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 19/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 20/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 21/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 22/30... Test Accuracy - 0.7386 (65/88 correct predictions)
Iteration 23/30... Test Accuracy - 0.7386 (65/88 correct predictions)
...
Mean Accuracy:          0.7386
Standard Deviation:      0.0000
95% Confidence Interval: [0.7386, 0.7386]
=====
    
```

Global Phase: $478.30748150904566 + 2\pi \times [0] + 2\pi \times [1] + 2\pi \times [2] + 2\pi \times [3] + (\pi + \pi[1]) \times (\pi + \pi[0]) + (\pi + \pi[2]) \times (\pi + \pi[1]) + (\pi + \pi[3]) \times (\pi + \pi[2]) + (\pi + \pi[1]) \times (\pi + \pi[0]) + (\pi + \pi[2]) \times (\pi + \pi[1]) + (\pi + \pi[3]) \times (\pi + \pi[2])$



Challenges

Feature Selection

Parameter Selection

Data Mapping

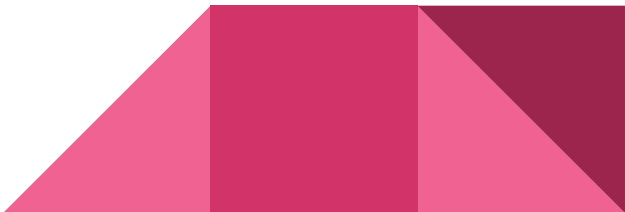
Circuit Architecture

Cost Minimisation

Noise Handling

Set up and run on QPU

Contributions

- **Adrian Șofariu – data embedding and model concept**
 - **Sebastian Șoptelea – data embedding and model concept**
 - **Rodica Ioana Lung – optimization and cost minimisation**
 - **Gheorghe Mahu – testing and validation**
 - **Tudor-Dan Mihoc – testing and presentation**
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Thank you for your attention!