Multi-Task Quantum Annealing for Rapid Multi-Class Classification

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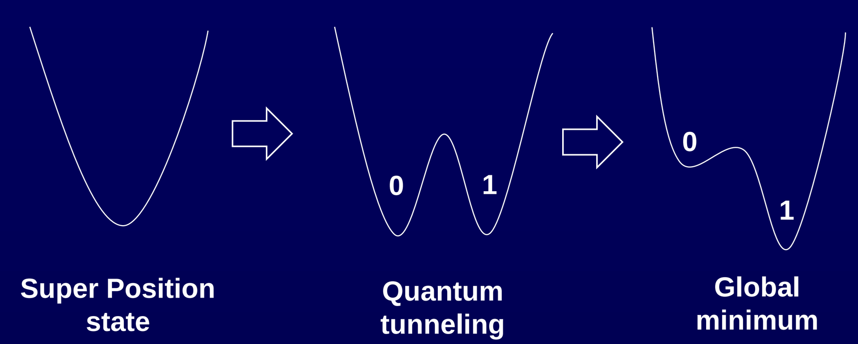
1. Introduction: Quantum annealing and Support Vector Machines

Quantum annealing

S. Boixo et al., Nature Phys. 10 (2014) 218.

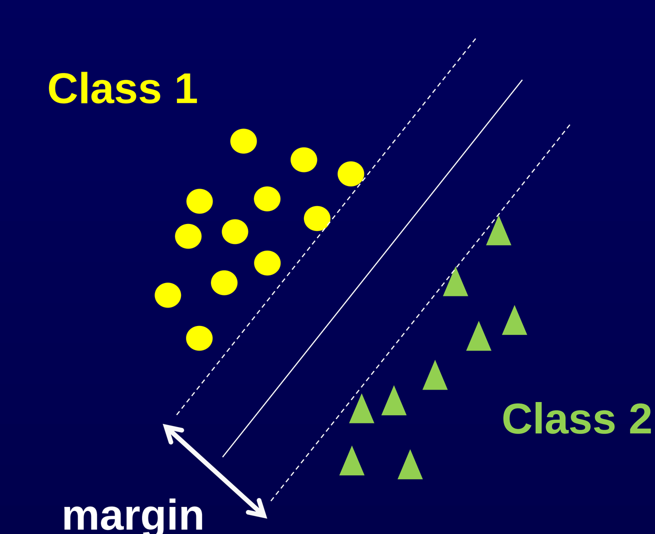
D-Wave Systems:

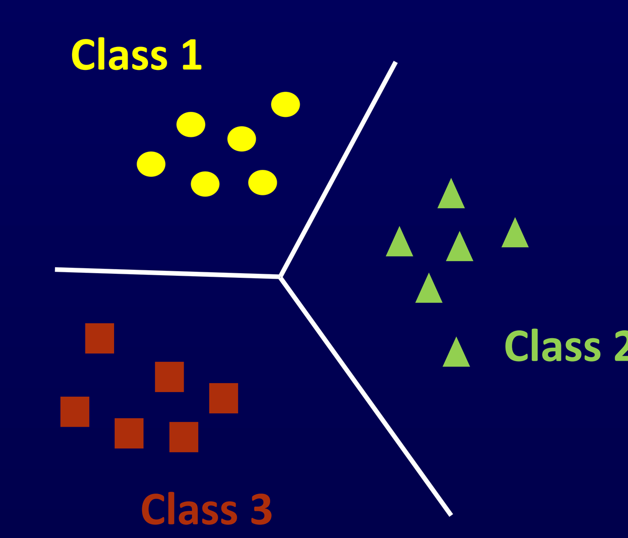
- Flux Quantum Bits
- Ultra Low Temperature
- More Than 5000 Qubits
- Quantum Annealing



Real-World ⇨ Mathematical Modeling ⇨ Quantum Annealer ⇨ Real-World

Multi-Class Classification SVMs





We employed OnevsRest strategy.

2. Rapid Multi-Class Classification Using D-Wave Quantum Annealer

SVM Quantum formulation

Real value to Binary encoder:

$$\alpha_n = \sum_{k=0}^{K-1} 2^k a_{Kn+k}$$

$a_{Kn+k} \epsilon \{0,1\}$: Binary Variable

$y_{i,j}$ is class label, $k(x_i, x_j)$ is the kernel function

QUBO (Quadratic Unconstrained Binary Optimization):

$$\underbrace{\sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{N} y_i y_j \alpha_i \alpha_j k(x_i, x_j)}_{\text{maximizing the margin}} + \underbrace{\left(\sum_{i=1}^{N} y_i \alpha_i\right)^2}_{\text{class constraints}}$$

$y_{i,j}$ is class label

$k(x_i, x_j)$ is the kernel function, we used rbf kernel

N is class number

For each classifier in our study, a Quadratic Unconstrained Binary Optimization (QUBO) problem is formulated. This QUBO is then mapped directly onto a quantum annealer, allowing us to leverage the device's capabilities to optimize the solution. This process ensures that each classifier is efficiently tailored to maximize classification accuracy by finding the optimal hyperplane in the high-dimensional space.

Multi-tasking Quantum Annealing

OneVsRest strategy:

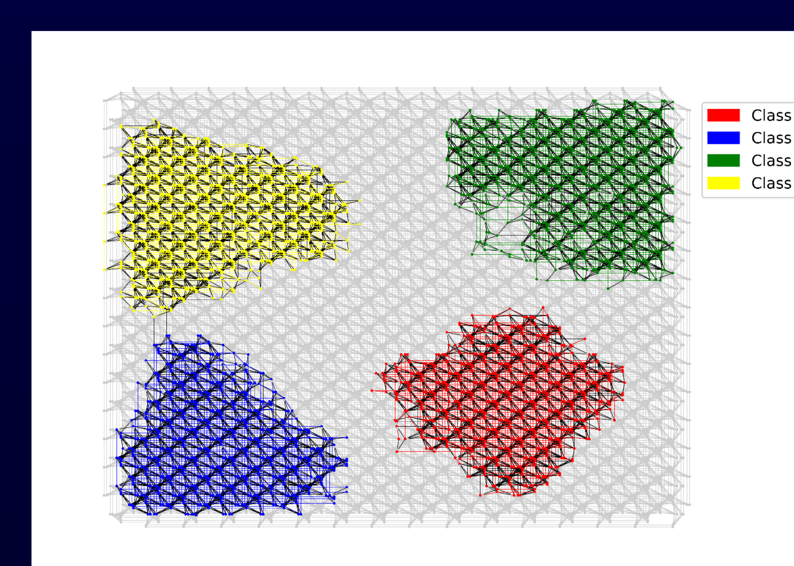
"Winner-takes-all"

Classifier	Output
C1 vs Rest	Not C1
C2 vs Rest	Not C2
C3 vs Rest	C3
Result	C3

Classifier	Output
C1 vs Rest	-120
C2 vs Rest	-100
C3 vs Rest	Not C3
Result	C1

Need to train N (number of classes) classifiers

Parallel Quantum Annealing



Hamiltonian combining into one:

$$H_{total} = \begin{bmatrix} H_1 & 0 & 0 & 0 \\ 0 & H_2 & 0 & 0 \\ 0 & 0 & H_3 & 0 \\ 0 & 0 & 0 & H_4 \end{bmatrix} \Longrightarrow [H_1, H_2, H_3, H_4]$$

Sequential Quantum Annealing

QA runs with the same embedding allocation for each classifier. In total, N run for training.

Example on left

Class 0 vs Rest
Class 1 vs Rest
Class 2 vs Rest
Class 3 vs Rest

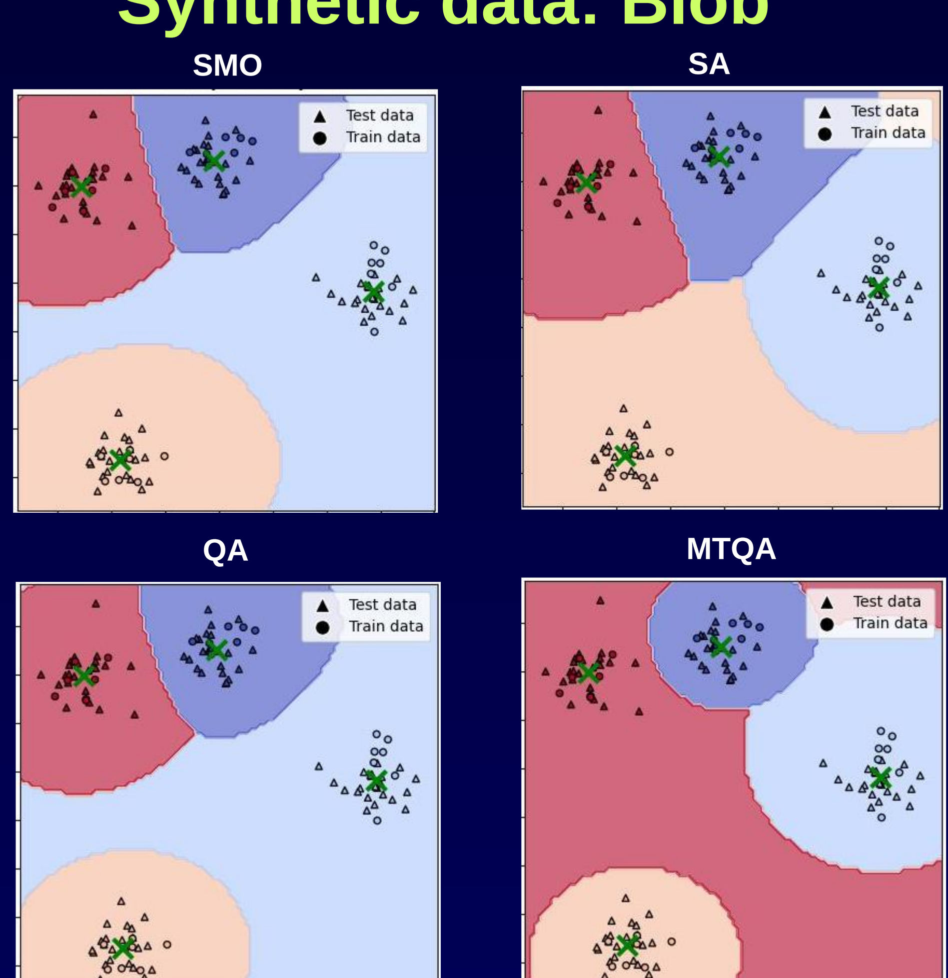
QA run 4 times

Decoding into each classifier

The processes of combining and decoding are performed on the CPU for computation.

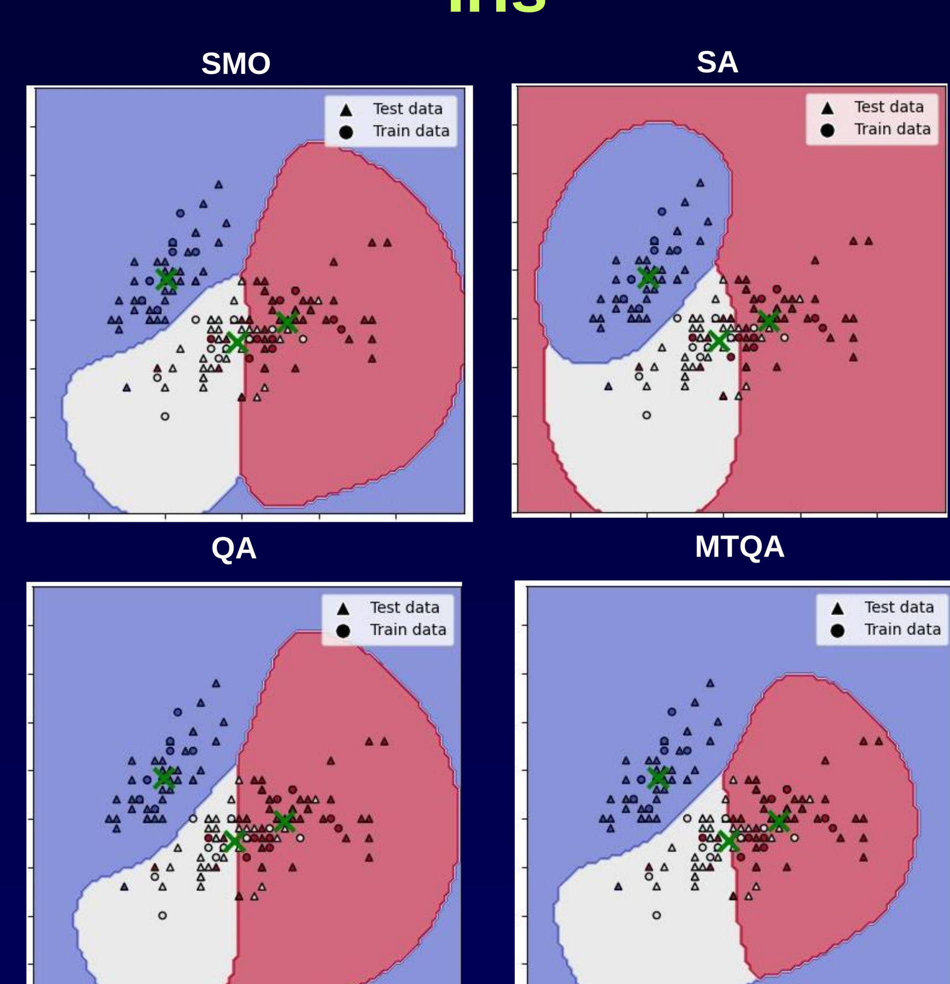
3. Experimental Results

Synthetic data: Blob



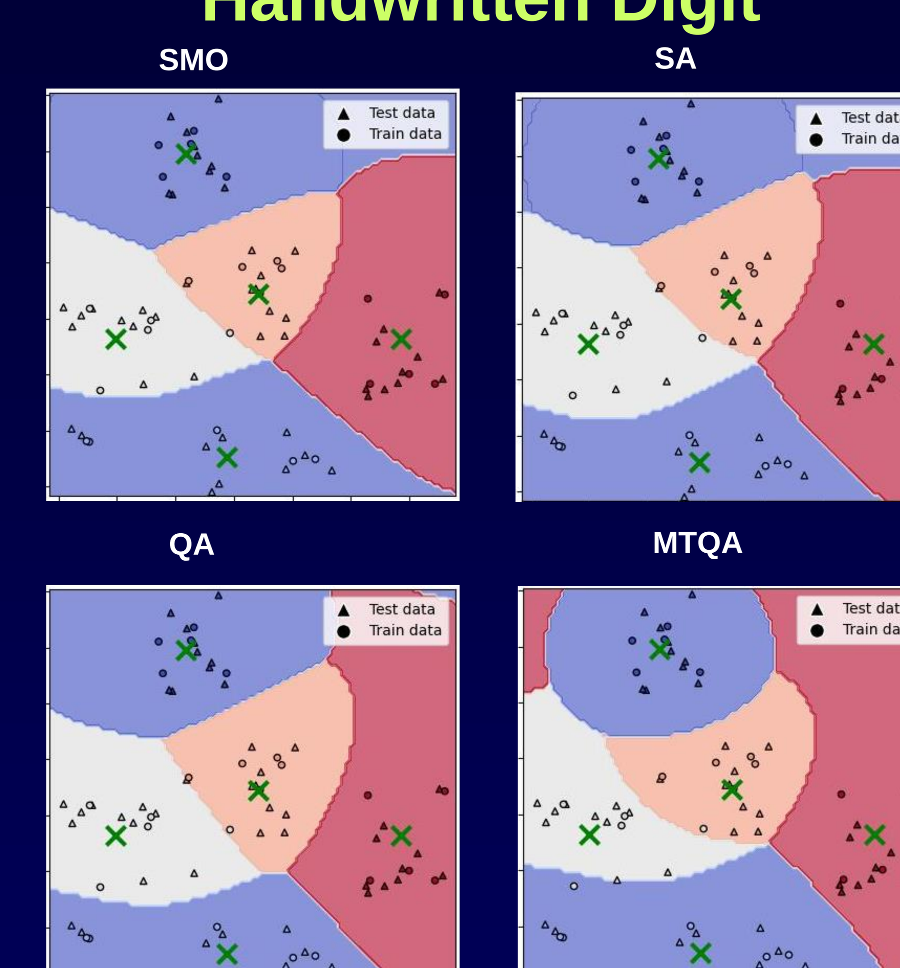
In the Blob dataset with four classes, MTQA matched the perfect 100% accuracy achieved by SMO, SA, and QA, confirming its capability to efficiently manage straightforward classification tasks without compromising on performance.

Iris



Despite the challenging nature of the Iris sepal dataset, MTQA closely approached the accuracy levels of SMO and SA, with slight reductions in testing accuracy suggesting areas for further optimization and robustness in feature-sensitive datasets.

Handwritten Digit



For the handwritten digits 0 to 4, MTQA showcased a strong performance, aligning closely with SMO and SA in accuracy while demonstrating its potential to efficiently handle more complex, multi-class recognition tasks in real-world applications.

4. Conclusions

- Efficiency Enhanced: Multi-tasking Quantum Annealing (MTQA) significantly reduces quantum processing cycles required for multi-class SVM classification, enhancing computational efficiency.
- Accuracy Maintained: MTQA maintains accuracy levels comparable to traditional methods, effectively handling multiple classification tasks simultaneously on quantum hardware.
- Future Potential: The success of MTQA in this study demonstrates its potential to transform machine learning applications, paving the way for advanced quantum computing solutions in complex data classification.