Quantum Algorithms for Earth Observation Image Processing

Abstract

Satellite-based Earth observations have a broad range of applications, such as natural disaster warnings, analysis of global temperature impacts, weather conditions analysis, and land-use classification. However, current machine learning techniques for land-use classification are costly in terms of time and energy. There two possible approaches to solving this problem. The first one are Variational Quantum Algorithms. They are a class of quantum algorithms that is aimed at the application in the Near Intermediate-Scale Quantum computing era. These algorithms employ jointly parametrized quantum circuits and classical optimization techniques for finding quantum circuits or states that have desirable properties from the point of a given application. VQAs find applications typically in finding low energy states of quantum Hamiltonians, solving approximately Quadratic Unconstrained Binary Optimization problems and training Quantum Neural Networks. In the area of Earth observations, the most promising area of applications lies with QNNs since the application of VQAs allows for the creation of new classification methods that employ quantum information processing tools. The second approach is to use quantum computers for a hybrid machine-learning approach utilizing an autoencoder for dimensionality reduction and a quantum algorithm powered by quantum annealer to reduce training costs. The autoencoder, using conventional deep learning techniques, is executed on GPUs, while the Deep Belief Network is run on a D-Wave quantum annealer. This hybrid approach allows for independent training of both modules, partially reducing the time and energy required to retrain the model.

21 EO use-case problem description

Distinct sensors on the satellite platforms and aircraft monitor Earth's surface day and night. They produce and transfer several terabytes of raw EO data to data storage on the ground. The stored data are only relevant when processed. Currently, deep learning becomes an indispensable tool for extracting informative information from raw EO datasets. Unfortunately, training large deep-learning neural networks is costly and consumes a significant amount of energy. Therefore, it is desirable to assess the possibility of the application of quantum computers for tasks related to processing EO data. Typical tasks related to EO data processing are mostly related to image classification or segmentation. It was shown that quantum algorithms can perform these tasks on EO data Gawron and Lewiński [2020]; Gupta et al. [2022, 2023]. In particular, Variational Quantum Algorithms are suitable and applicable in the area of EO data classification. It was shown rigorously Gyurik and Dunjko [2022] that quantum machine learning methods can have advantages over their classical counterparts. Therefore, there may exist substantial advantages for their application for EO data processing.

Satellite-based Earth observations have a broad spectrum of use cases Kansakar and Hossain [2016], Zhao et al. [2022]. This naturally leads to a wide range of potential real-life applications. Those include tasks related to various important "how to" questions such as how to

1. warn people against natural disasters (e.g. floods, fires),
2. analyse the impact of rising global temperatures on ocean levels and rate of glacier melting.

3. analyse weather conditions (e.g., for optimizing the localization of green energy installations)
4. analyze the structure of crops,
5. perform assessment of forest area in different countries and identification of areas of heavy defrostation.

Potential answers/solutions, especially those leading to sustainable development, require a constant flow of information regarding environmental changes. Currently, machine learning techniques for land-use classification of the Earth's surface often employ (deep) neural networks. While those networks are very efficient in a variety of human-like tasks, they are very costly to train (in terms of time and energy). This naturally calls for an investigation to what extent it is possible to offload the training process to a quantum computer to reduce the training costs.

22 Vartiational quantum algorithms

22.1 Introduction

Variational quantum algorithms (VQA) are a class of quantum-classical heuristics that employ both classical computers and quantum computers to perform optimization of a function computed using a quantum computer. The main idea behind VQA is as follows. The algorithm designer chooses a class of parametrized quantum circuits that can be executed on a quantum computer and an observable that can be measured on this computer. The goal of computation is to find such parameters of the quantum circuits that generate the state for which the expectation value of this observable is optimized. The optimization procedure is performed by iterative varying of the parameters, executing the quantum circuit, and measuring the expectation value of the observable. This procedure is controlled by the classical computer and repeated until a given stop criterion is reached.

Variational quantum algorithms can be applied to:

- solving (approximately) Quadratic Unconstrained Binary Optimization (QUBO) Farhi and Harrow [2016] problems using Quantum Adiabatic Optimization Algorithm (QAOA) Farhi and Harrow [2016],
- minimizing the energy of quantum Hamiltonian — Variational Quantum Eigensolver (VQE) Peruzzo et al. [2014], and
- training Quantum Neural Networks (QNNs).

22.2 Technical description

The mathematical formulation of a VQA is the following. Given an initial state $|\psi\rangle \in \mathbb{C}^n$, parametrized quantum circuit $U(\theta) \in \mathbb{C}^{n\times n}$, an observable $O \in \mathbb{C}^{n\times n}$ the goal is to find such a set of parameters θ that minimizes the expectation value of observable O in the state $U(\theta)|\psi\rangle$ *i.e.* $\langle O\rangle_{U(\theta)|\psi\rangle} = \langle\psi| U^\dagger(\theta) O U(\theta)|\psi\rangle$. The optimization is performed using a classical computer by varying the parameters θ and minimizing the function $f(\theta) := \langle O\rangle_{U(\theta)|\psi\rangle}$.

There exist variations of the abovementioned algorithm that can be adapted to a variety of tasks.

22.2.1 Parametrized quantum circuits

A common technique to implement Variational Quantum Algorithms is to employ Parametrized Quantum Circuits (PQC). PQC $U(\theta) = (U(\theta_i))_{i=1}^N$ is a sequence of N quantum gates that depend on one or more real-valued parameters θ_i. Once the parameters are defined the PQC becomes an ordinary quantum circuit that can be—in principle—executed on a quantum machine.

22.2.2 Variational Quantum Eigensolver

The Variational Quantum Eigensolver is the most important example of VQAs because it provides an approximate solution to the problem of finding the ground state of a quantum Hamiltonian that can be expressed in the following way. Given Hamiltonian H find its minimal eigenvalue E_{min} (minimal energy) and minimizing eigenvector $|\psi_{\text{min}}\rangle$ (minimal energy state). It is known that for any quantum state $|\psi\rangle \geq E_{\text{min}}$. Therefore, one can find an approximate value of E_{min} by minimizing $\langle H \rangle_{U(\theta)|0\rangle}$ by varying parameters θ of a PQC $U(\theta)$. To perform this operation on a quantum the Hamiltonian H has to be decomposed into a linear combination $H = \sum_\alpha h_\alpha P_\alpha$ of Pauli strings $P_\alpha = \sigma_1^{\alpha_1} \otimes \sigma_2^{\alpha_2} \otimes \ldots \otimes \sigma_N^{\alpha_N}$ with $\sigma_i^j \in \{\mathbb{1}_i, \sigma_i^x, \sigma_i^y, \sigma_i^z\}$, so that $\langle H \rangle_{U(\theta)|0\rangle} = \sum_\alpha h_\alpha \langle P_\alpha \rangle_{U(\theta)|0\rangle}$. The quantum circuit $U(\theta)$ should ideally dependent on a few parameters θ, be able to explore the Hilbert space of the quantum system, and be efficiently implementable on the quantum computer.

22.2.3 Quantum Neural Networks

Quantum Neural Networks (QNNs) are a class of machine-learning models that can be evaluated on a quantum computer. QNNs, similarly to classical neural networks are parametrized functions that can be trained using data to perform common machine learning tasks such as classification, regression, sampling from a complex probability distribution or generating new data. QNNs can be composed—in the mathematical sense—with classical neural networks forming hybrid quantum-classical NNs and jointly trained using backpropagation.

The visual representation of a quantum variational algorithm that employs both data x and parameters θ is presented in Fig. 15. In the figure, the quantum computer is driven by the classical computer that is responsible for transferring the data x and parameters θ to the controller of the quantum computer that uses these pieces of information to generate quantum circuits $U^{(k)}_{\text{load}}(x)$ and $U^{(k)}_{\text{var}}(\theta)$ that encode data and model respectively. After those circuits are executed measurements of quantum observables O_i is performed and the outcomes of the measurements $f_i(x, \theta)$ are returned to the classical computer and combined jointly using—possibly parametrized—function $f_{\text{classical}}(f_1(x, \theta_1), \ldots, f_I(x, \theta_I), \theta_{\text{classical}})$.

A typical implementation of the forward part of the training of a quantum neural network is presented in Algorithm 1.

Algorithm 1 Forward algorithm for a quantum neural network.

```
procedure FORWARD(x, θ)
    for k = [K] do                                  ▷ Repeat for each QNN layer
        APPEND(Q_tape, U_var^(k)(θ))                ▷ Append the variational circuit to the tape
        APPEND(Q_tape, U_load^(k)(x))               ▷ Append the data loading circuit to the tape
    APPEND(Q_tape, O)                               ▷ Append observable O to the tape
    f(x, θ) ← QCRUN(Q_tape)                         ▷ Execute quantum tape and measure results
    return f(x, θ)
```

Data encoding Classical data can be encoded on the computational basis of quantum states—as binary strings, amplitudes of the quantum states or observables.

Quantum neural network architectures Quantum neural networks can be implemented in a variety of architectures. The simplest case is when the quantum evolution is completely unitary e.g. Figure 16b presents

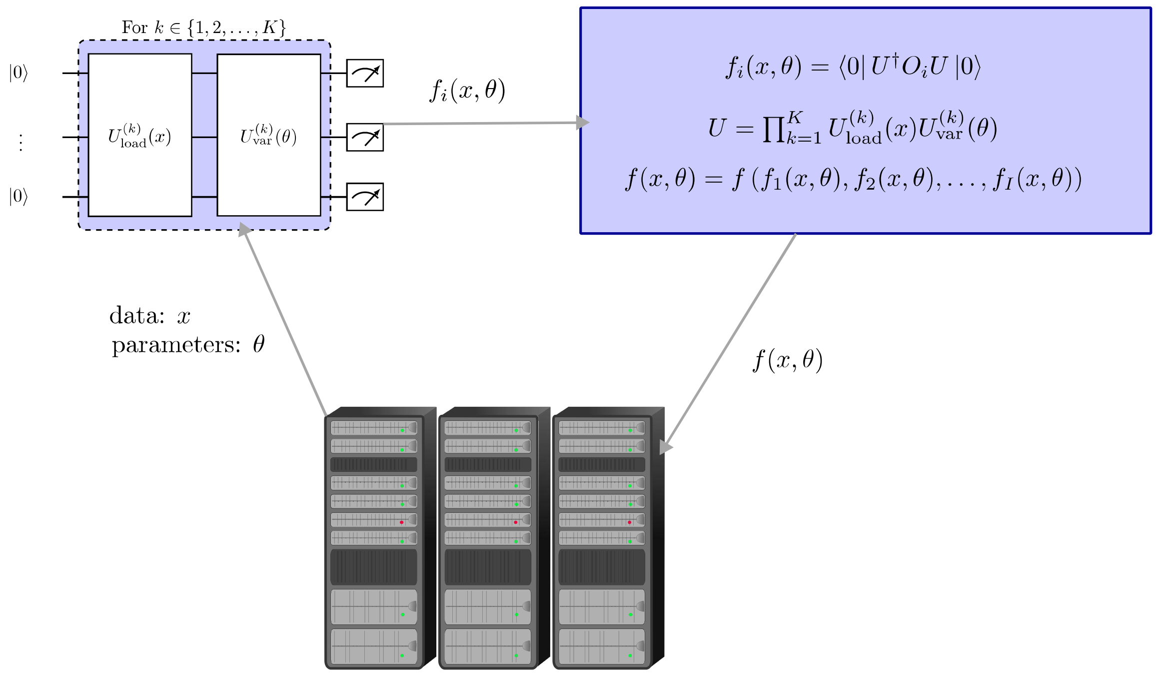
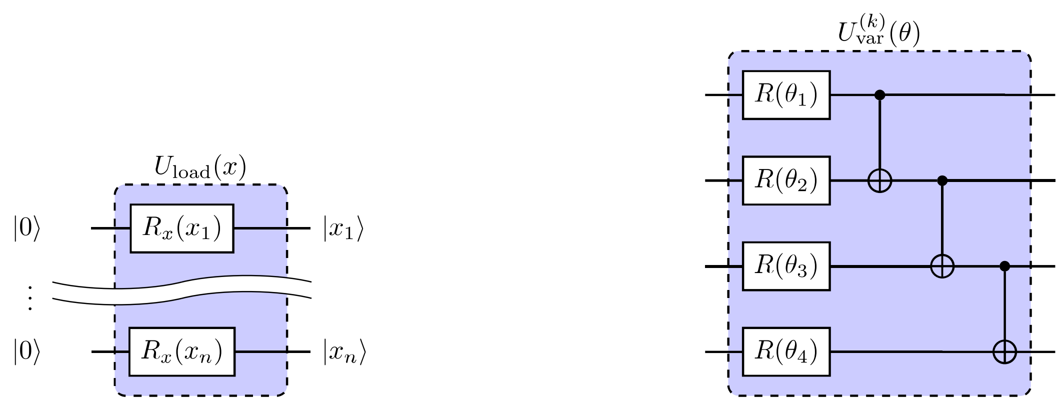


Figure 15: A simple depiction of QNN main quantum loop.



(a) QC for loading of classical data to a quantum computer.

(b) An example of a quantum neural network layer.

an example of a simple layer of a quantum neural network with general parametrized qubit rotations being controlled by the model parameters.

Other architectures can introduce mid-evolution measurements and classically controlled gates or extending the number of used qubits in subsequent layers of QNN.

22.2.4 Quantum Adiabatic Optimization Algorithm

Quantum Adiabatic Optimization Algorithm QAOA uses the VQA principle to solve, possibly approximately Quadratic Unconstrained Optimization (QUBO) problems. The algorithm does it by simulating the adiabatic quantum computing process.

There exist several issues related to each of the steps of the above algorithm. The architecture of a quantum computer and the structure of a particular problem have to be taken into account while designing and executing a VQA. Additionally, it is important to take into the account the interplay between the classical computing systems: storage, information transfer and compute units with the quantum computer.

22.3 Sizing quantum machines for VQAs

Authors of an in-depth overview Bharti et al. [2022] provide an overview of the current state of quantum computers concerning implementations of VQAs as well as an outlook for the future. They divide the future into two main eras: one of near intermediate-scale quantum computer NISQ and one of the fully error-corrected quantum (FEC) computers. Unfortunately, they do not attempt to provide any concrete timeline for the possible future development of VQAs. Since the efficiency of variational quantum algorithms depends on multiple factors, such as:

- number of qubits,
- qubits connectivity,
- single-qubit, two-qubit or multi-qubit gate fidelities,
- measurement errors,
- quantum system coherence time,
- execution time of operations reset, gate, and measurement,
- scalability of the quantum computing hardware platform,
- precision of control pulses,
- possibility to perform mid-quantum computing measurement and classical computing,
- classical optimization method,
- ansatze,

the following sizing assessment is an educated guess about the timeline for future VQAs applicability to real-life problems related to EOs.

We can use the method for defining practical quantum advantage and application readiness levels (ARLs) as presented recently by Herrmann et al. [2023]. The authors define quantum advantage using the notions of quantum utility or quantum dominance, where the former notion requires that a quantum (possibly hybrid) system "(i) requires less computing time, or (ii) requires less power, or (iii) yields more accurate results [...] to the best classical device of similar size, weight, and cost.", and the latter notion requires that points (i)–(iii) are "compared to any other classical device".

The authors of Herrmann et al. [2023] define five levels of application readiness levels:

- ARL 1: concept with unknown potential,
- ARL 2: beneficial in small idealized systems,
- ARL 3: utility indicated by theory or resource estimations,
- ARL 4: simulated utility demonstration,
- ARL 5: utility demonstration on quantum hardware.

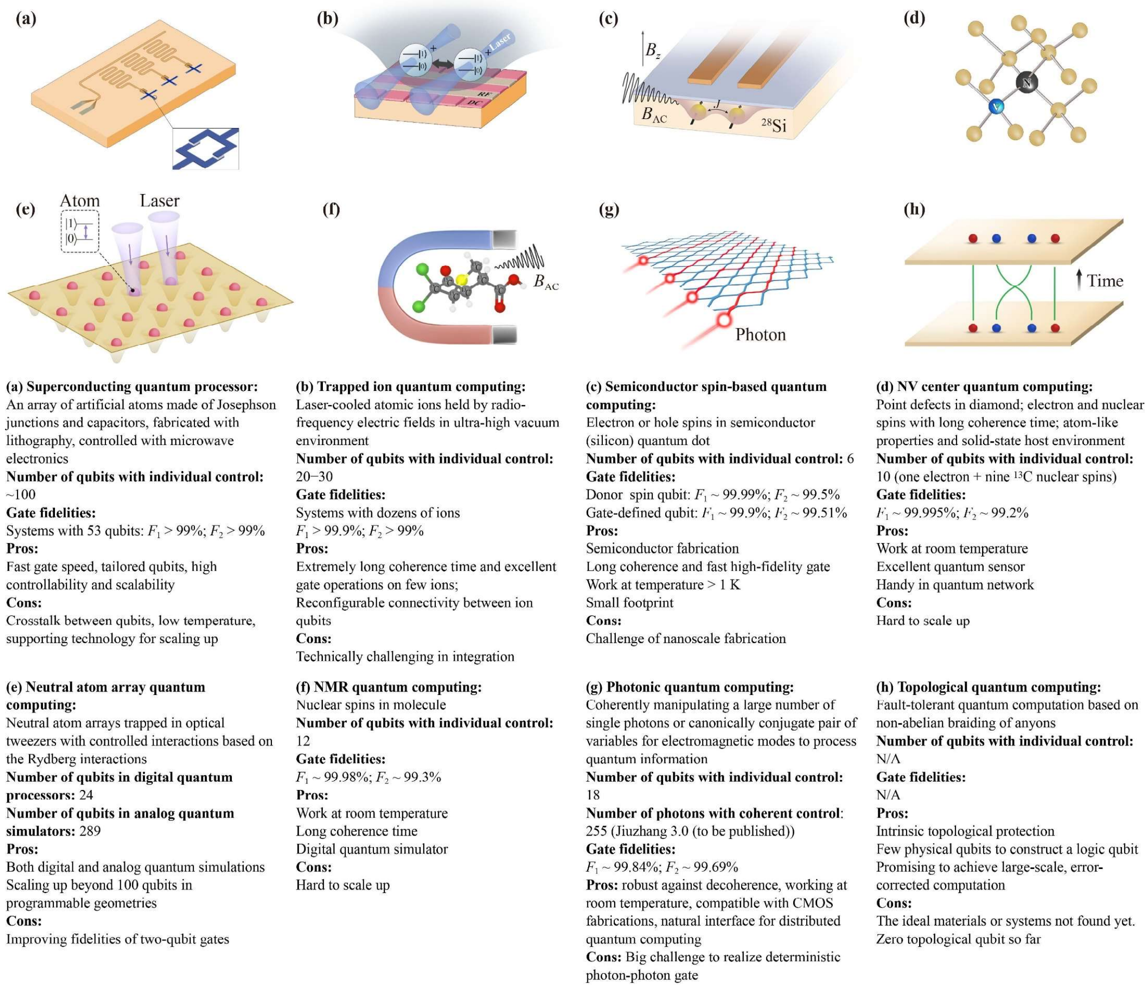


Figure 17: Reproduction of Fig. 2 from Cheng et al. [2023b] presenting a selection of quantum computing hardware. (CC-BY 4.0)

22.3.1 Currently

Currently-existing quantum computers belong to the NISQ era and can not claim any applicable advantage over classical computers. Those are experimental devices testing the limits of the existing technology. Decoherence, limited qubit connectivity, gate errors and measurement errors. The training of a QNN on a quantum computer is currently very difficult and not efficient.

We have currently reached ARL level of one for most VQAs applications. There exists several proposals of applying VQAs for remote sensing data processing such as e.g. Gawron and Lewiński [2020]; Gupta et al. [2022, 2023]; Nalepa et al. [2022]; Miroszewski et al. [2023]; Otgonbaatar and Datcu [2021b,c], and also for EO mission planning Rainjonneau et al. [2023].

22.3.2 3–5 years

It is unlikely that any neither useful implementation of a Variational Quantum Eigensolver or Quantum Machine Learning algorithm will be demonstrated. The quality of the quantum computers will be too low. But we can observe steady progress in the quality of quantum hardware, the development of new practical algorithmic ideas, and the development of quantum software stack.

After the mark of five years, we should be able to achieve ARL of two or three for at least a couple of VQAs use cases if major efforts are put into R&D activities.

22.3.3 15 years

While it is very difficult to predict the future of disruptive technology, such as quantum computing, 15 years ahead one can hope for the existence of fully error-corrected quantum (FEC) computers with hundreds of logical qubits. Such computers would be able to tackle machine learning problems that are impossible to be solved today. Especially if supplied with coherent quantum information e.g. acquired from quantum sensors.

After the mark of 15 years, we can be hopeful to show ARL four or five for at least one or two use cases.

22.4 SWOT analysis

22.4.1 Strengths

- Quantum Neural Networks have larger effective dimensions than Deep learning models Abbas et al. [2021].
- Quantum kernel methods can provide better classification results by transforming quantum encoded features using projected quantum kernels than classical kernel methods Huang et al. [2021].
- Quantum Born machines could be applied to generate data samples from classically difficult distributions Coyle et al. [2020].
- Proved exponential speed-up in at least one scenario Liu et al. [2021].

22.4.2 Weaknesses

- Data loading is a major obstacle for achieving exponential speed-up of some QML algorithms Tang [2021b].
- Limited number of samples obtained from quantum devices leads to measure concentration Thanasilp et al. [2022] and difficulty to train quantum kernel methods.
- Measurement error mitigation is limited very strongly by the number of qubits and the circuit depth. Quek et al. [2022].
- VQAs can be difficult to train due to barren plateaus McClean et al. [2018].
- Noisy quantum devices have major limitations Stilck França and García-Patrón [2021].

22.4.3 Opportunities

- Major shift in the quality of quantum computers. Fully-error corrected quantum computer available with ≈ 100 fully error qubits.
- New applications of classical machine learning for quantum computing: compiling, mapping, control, error correction.

22.4.4 Threats

- Fundamental lack of ability to control, mitigate and correct sources of noise in the QCs.
- Unlikely collapse of the complexity hierarchy will likely lead to a lack of quantum advantage.
- Potential new “no-go theorems”.

23 Hybrid approach

23.1 Introduction

We propose an autoencoder for the dimensionality reduction of input EO images, and a quantum algorithm powered by the quantum annealer (quantum machines) to reduce the training costs. Ideally, in such a hybrid machine-learning approach, one would want to combine at least two distinct modules. The first one is precisely an autoencoder, with latent binary representation, that essentially prepares data to be used by the (quantum) annealer. The second is a Deep Belief Network, a stack of Restricted Boltzmann Machines, which is used for classification purposes Hua et al. [2015], Dixit et al. [2020], Dixit et al. [2021]. The crucial part related to the training of every neural network is an update of all connections between neurons. This process involves calculating many average values of specific functions (which are problem-dependent). The computation can be accelerated if one can sample from a particular distribution, which again is problem-dependent. Then, and only then, all complicated expectations values involving that distribution simplify to weighted sums. This is precisely what a quantum annealer allows one to do. Independent samples can be drawn from the Boltzmann distribution quickly (even in microseconds), accelerating the training stage. However, to take advantage of such capabilities, one needs to (re)formulate the original classification problem using the Ising Hamiltonian (a model of interacting spin-1/2 particles). How to perform such a mapping effectively is an open problem, being part of this study. Interestingly, both modules of such hybrid architecture can be trained independently. The autoencoder, which uses conventional deep learning techniques, can be executed on the GPUs, and the second one — deep belief network — on the D-Wave quantum annealer. This separation allows us to partially reduce the amount of time and energy needed to retrain the model.

23.2 Technical description

As a proof-of-concept of our approach, we also provide pretrained models for a selected set of data. The solution consist of a machine learning system. The client will be able to request the training of its model on the Sentinel-2 multispectral data they select and demand the land-use labels for a particular set of land patches. The solution uses the D-Wave quantum annealer during the training process. The annealer is used in the most difficult part of the machine learning pipeline. Namely, in generation of the multispectral data representation and multilabel classification. We aim to use a two-stage data transformation process. In the first stage, the data will be transformed from its natural representation into a binary sequence, which is more natural for quantum machines. This binary string should encode most of the relevant information about a hyperspectral data cube patch.

The processing pipeline of the presented approach is as follows (see Figure 18).

First, the multispectral data is compressed into a binary representation using an autoencoder schematically presented in Figure 19. We considered two autoencoders, like latent Bernoulli autoencoder (LBAE) and Binary variational autoencoder (BVAE). The LBAE model is used as an example in the compiled version of our solution. As such, it will be discussed in greater detail in the following.

Then the compressed data are used to train a restricted Boltzmann machine (RBM). We consider three possible training backends for this process:

- Contrastive divergence (run on a classical computer).

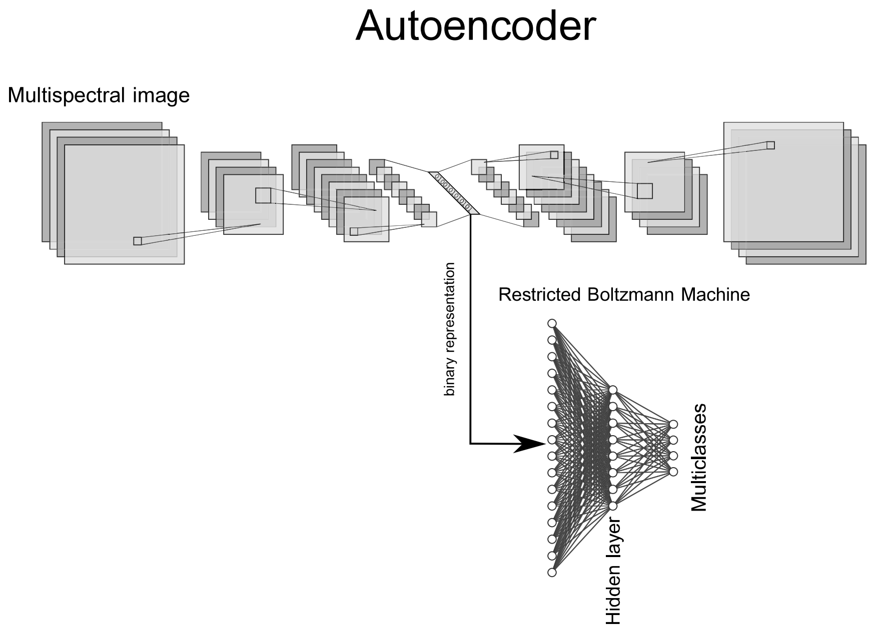


Figure 18: Processing pipeline of hybrid machine-learning approach based on autoencoder and RBM.

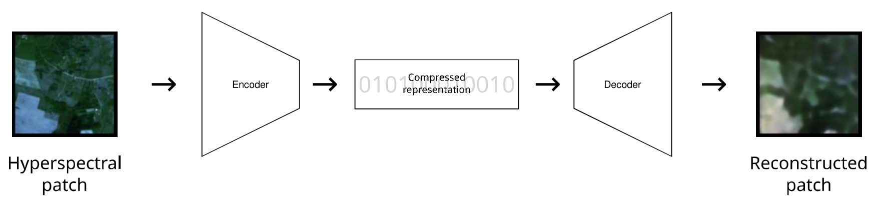


Figure 19: Processing pipeline of the LBAE training.

- Coherent Ising machine (CIM). This approach takes as an input an Ising optimization problem and solves it using a system of dynamical equations resulting in a simulation of the behavior of an actual quantum annealer. A general overview of CIM is presented in the following subsections.
- Quantum annealing backend. Currently, this backend uses the D-Wave annealer. A short note on utilization of quantum annealers is presented in the following subsections.

In the next step of the weights obtained form the training of the RBM are used as weights for layers of a neural network.

Lastly, we train the final layer of our network in a supervised manner. All other weights remain fixed. This is the only supervised part of our training pipelie.

23.2.1 Latent Bernoulli autoencoder

The need for differentiability of each layer represents a challenge if one desires to train stochastic neurons or other non-differentiable functions such as quantization Fajtl et al. [2020]. Sampling from and interpolating in the discrete latent space is equally challenging. Unlike multimodal, Gaussian and many other real-valued distributions, the multivariate Bernoulli distribution concentrates most of the information on the second and higher moments, since the marginals are strictly unimodal and entirely described by the mean. Given that this model learns a distribution with unknown prior, and based on the aforementioned premise, the model parametrizes the learned distribution by its first two moments. The main advantage of the model is the fact that there is no sampling of pseudo-random numbers during the training step.

23.2.2 Coherent Ising machine

The coherent Ising machine is an iterative algorithm for sampling low-energy spin configurations in the classical Ising model Goto et al. [2021]. It treats each spin value as a continuous variable from the range $[-1, 1]$. Each iteration begins with calculating the mean field acting on each spin by all other spins. Then the gradients for the spin values are calculated. Then the spin values are updated according to the gradients and some chosen activation function. After multiple updates, the spins will tend to either -1 or +1 and the final discrete spin configuration is obtained by taking the sign of the continuous variables. CIM has been tested on a variety of problems. Implemented on a consumer graphic processor, this algorithm runs faster and generates higher quality samples than many analogue and digital annealing processes. Typical results from these simulations are presented below (see Figure 20).

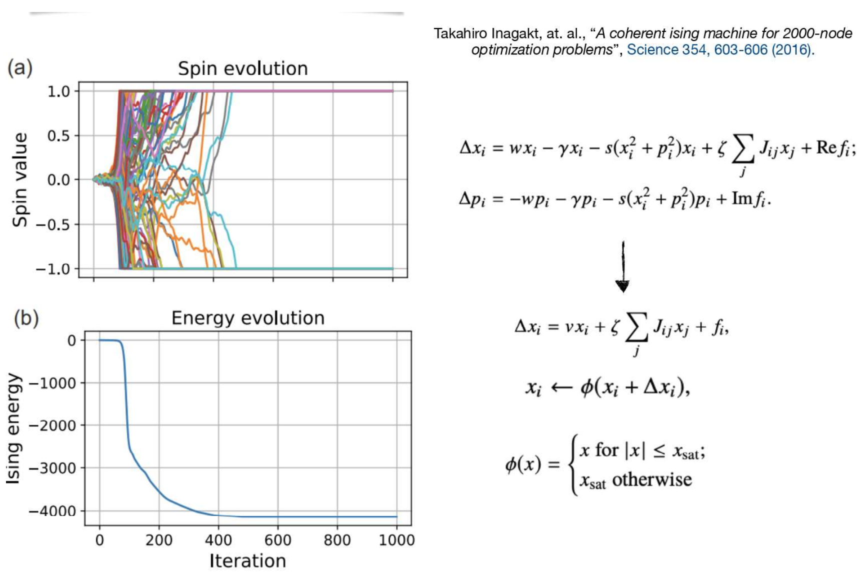


Figure 20: Results from simulations of training a restricted Boltzmann machine with training backend based on coherent Ising machine.

23.2.3 D-Wave annealer

The quantum annealer allows us to sample from the Boltzmann distribution, which is a crucial part of training an RBM Dixit et al. [2021]. With the rapid advancement of this technology (see Figure 21) this shows a great promise for acceleration of classical training.

The learning process is a hybrid of classical and quantum computation. The weights of the RBM are stored on a classical computer and are updated based on samples from the Boltzmann distribution obtained from the quantum annealer. This can be summarized as

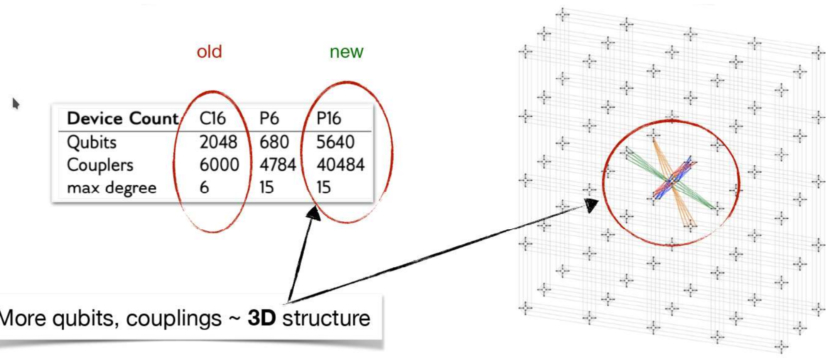


Figure 21: Figure show comparison of parameters D-wave architectures like Chimera and Pegasus.

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial J_{ij}} &= \sum_{\mathrm{S}} \left(s_i s_j - \langle s_i s_j \rangle_{\{\mathrm{S}\}}\right) & & \Delta \hat{J} \approx \xi\left(\frac{1}{N}\sum_{n=1}^{N} \mathrm{s}_n \mathrm{s}_n^{\mathrm{T}} - \frac{1}{M}\sum_{m=1}^{M} \hat{\mathrm{s}}_m \hat{\mathrm{s}}_m^{\mathrm{T}}\right) \\
& & \longrightarrow & \\
\frac{\partial \mathcal{L}}{\partial b_i} &= \sum_{\mathrm{S}} \left(s_i - \langle s_i \rangle_{\{\mathrm{S}\}}\right) & & \Delta b \approx \xi\left(\frac{1}{N}\sum_{n=1}^{N} \mathrm{s}_n - \frac{1}{M}\sum_{m=1}^{M} \hat{\mathrm{s}}_m\right).
\end{aligned}
\tag{13}
$$

23.2.4 Hybrid approaches with simulated bifurcation machines

Hybrid quantum-classical optimization is an approach that combines classical optimization algorithms with quantum computing techniques to solve complex optimization problems more effectively. In the context of Simulated Bifurcation Machines (SBM), the idea is to use SBM as a quantum-inspired technique to complement classical optimization algorithms.

An (SBM) is a type of quantum-inspired computing technology designed to solve complex combinatorial optimization problems. It was developed by researchers at Toshiba, and it is based on the concept of bifurcation, which is a phenomenon in dynamical systems where a small change in a system's parameters can cause a sudden shift in its behaviour.

The SBM leverages a classical computer to simulate the behavior of a quantum system undergoing bifurcation. It uses this behavior to explore the solution space of the given optimization problem more efficiently than traditional classical methods. The key idea behind the SBM is to take advantage of the sudden transitions that occur in bifurcation to jump between possible solutions, allowing the algorithm to converge to an optimal or near-optimal solution quickly.

While the SBM is not a true quantum computer, it is inspired by and seeks to harness some of the benefits of quantum computing. This technology has shown promise in solving a variety of optimization problems, such as the traveling salesman problem, portfolio optimization, and drug discovery, among others. However, it is important to note that the SBM has its limitations and is not a universal solution for all optimization problems.

The technical aspects of a Simulated Bifurcation Machine (SBM) involve a combination of classical computing and concepts inspired by quantum mechanics. The underlying mechanism of SBM is based on the phenomenon of bifurcation, which is characterized by sudden changes in the behavior of dynamical systems. Here are some key technical aspects of SBM:

1. Hamiltonian dynamics: In SBM, the optimization problem is mapped to a continuous-time Hamiltonian system. A Hamiltonian function is used to describe the total energy of a system, which is the

sum of kinetic and potential energies. The Hamiltonian dynamics is used to navigate the solution space of the optimization problem Kalinin et al. [2021]; Goto [2021].

2. Simulated bifurcation algorithm: The SBM uses a simulated bifurcation algorithm that mimics the behavior of quantum systems undergoing bifurcation. The algorithm leverages the classical computer's ability to simulate these quantum-like transitions, allowing for an efficient exploration of the solution space Kalinin et al. [2021].

3. Adiabatic transitions: The SBM algorithm incorporates a concept similar to adiabatic quantum computing, where the system transitions slowly between different energy levels, staying close to the ground state. This allows the SBM to explore the solution landscape more efficiently Farhi et al. [2000].

4. Parameter tuning: In the SBM, the Hamiltonian system's parameters are carefully tuned to induce bifurcation points. These bifurcation points cause sudden transitions between different solutions, allowing the algorithm to jump from one solution to another and explore the solution space more effectively Kalinin et al. [2021].

5. Near-optimal solutions: The SBM is designed to find near-optimal solutions to combinatorial optimization problems. While it may not always find the absolute best solution, it can often find high-quality solutions in a relatively short amount of time compared to classical optimization algorithms Kalinin et al. [2021].

The Simulated Bifurcation Machine combines these technical aspects to provide an efficient, quantum-inspired approach to solving combinatorial optimization problems. However, it is important to note that the SBM has its limitations and is not a universal solution for all optimization problems Kalinin et al. [2021].

23.3 Sizing quantum machines for the hybrid approach

23.3.1 Currently

Currently-existing quantum annealers belong to the so-called NISQ era and can not claim any applicable advantage over classical computers. The current state of the art annealers has 5640 qubits and 40484 connections Systems [2023]. The device is susceptible to noise and for large families of instances, the device finds solutions far from the ground state.

23.3.2 3–5 years

D-Wave road map suggests that within 5 yeas the number of qubits will increase to around 8k and number of connection around 80k D-Wave Systems Inc. [2021]. The devices will still be prone to noise but it is likely that we will observe steady progress in the quality of the hardware. There will exist a hybrid (classical-quantum) solvers to solve large problems 1M variables. Those solvers will utilize sophisticated classical methods (simulated bifurcations) combined with quantum annealing.

23.3.3 15 years

In the forthcoming era, D-Wave quantum annealers will encompass 100,000 highly interconnected qubits, empowering them to address intricate optimization conundrums D-Wave Systems Inc. [2021]. Utilizing reversed annealing techniques will facilitate the generation of more sophisticated quantum states, while the hybrid solver methodology will amalgamate classical and quantum computing paradigms to ascertain optimal solutions. These cutting-edge developments will usher in unprecedented breakthroughs across domains such as optimization, machine learning, and logistics.

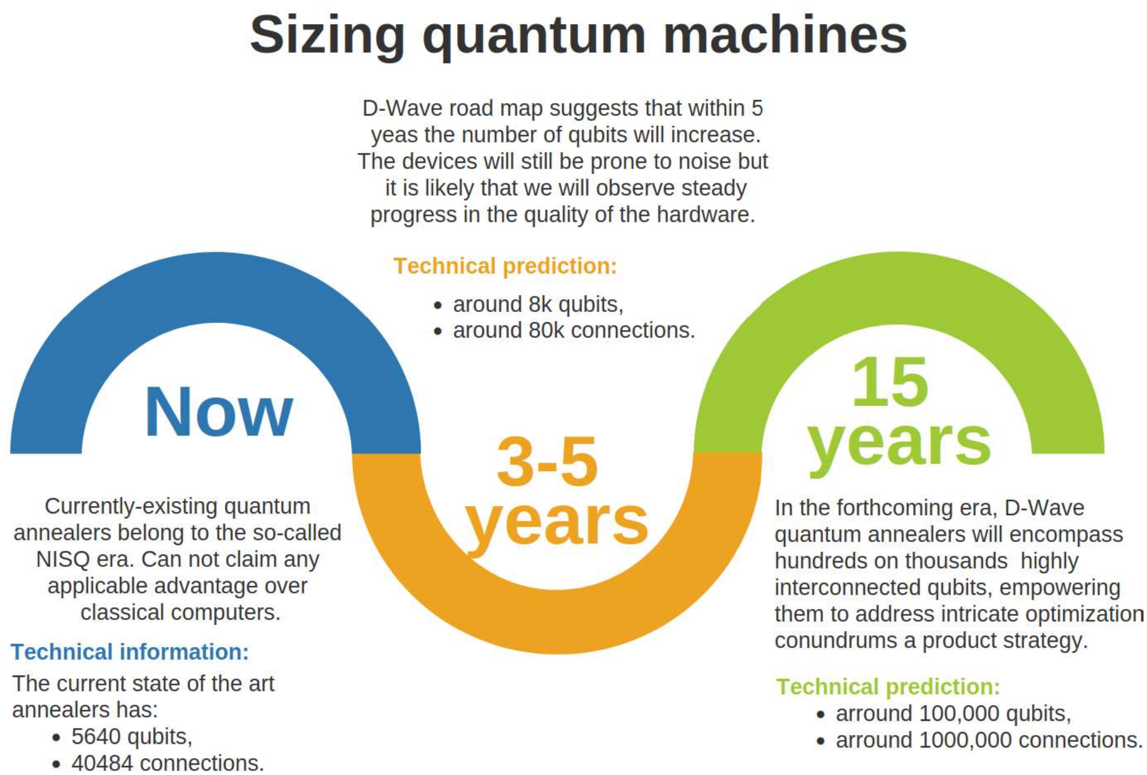


Figure 22: Figure shows sizing of quantum annealers

23.4 SWOT analysis

23.4.1 Strengths

- Quantum advantage: D-Wave annealers have the potential to process and analyze large amounts of data (utilizng hybrid approaches) significantly faster than classical computers Systems [2023].
- Hybrid solver approach: By combining classical and quantum computing methods, D-Wave's hybrid solvers can efficiently navigate the solution space and arrive at optimal or near-optimal solutions Systems [2023].
- Scalability: With 100,000 highly connected qubits, D-Wave quantum annealers can address increasingly complex Earth Land Cover Understanding problems as technology advances Systems [2023].

23.4.2 Weaknesses

- Noise sensitivity: Quantum systems, including D-Wave annealers, are susceptible to noise and errors, which may impact the accuracy of the results Preskill [2018b].
- Limited availability: D-Wave systems are not yet widely accessible, and their usage requires specialized knowledge and expertise Systems [2023].

- Problem-specific applicability: D-Wave annealers are primarily suited for optimization problems, which might limit their applicability in other aspects of Earth Land Cover Understanding Systems [2023].

23.4.3 Opportunities

- Enhanced remote sensing: D-Wave annealers can be applied to process and analyze remote sensing data, enabling more efficient and accurate land cover classification and monitoring Mallet and Bretar [2009].
- Climate change research: Quantum computing can potentially improve climate models and predictions, contributing to a better understanding of the impacts of land cover changes on the environment Biamonte et al. [2017].
- Interdisciplinary collaboration: The use of D-Wave annealers in Earth Land Cover Understanding can foster collaboration between researchers in quantum computing, remote sensing, and environmental sciences, leading to new insights and innovations.
- Hybrid approaches: Possibility to utiliza quantum-classical problems are split between a classical approach and the quantum annealer allows to tackle large problems.

23.4.4 Threats

- Competition: As more companies and researchers develop quantum computing technologies, there will be increased competition for D-Wave annealers in the Earth Land Cover Understanding domain Preskill [2018b].
- Technological obsolescence: The rapid pace of quantum computing advancements may render current D-Wave annealer technology obsolete or less competitive in the future Preskill [2018b].
- Funding constraints: The high costs associated with quantum computing research and infrastructure may limit the availability of funding for D-Wave annealer projects in Earth Land Cover Understanding.

24 Conclusions and recommendations

The only recommendation that can be provided is that further research is needed. It is important to identify bottlenecks where classical computers struggle to provide efficient solutions for the Earth Observations and try to pair them with the incoming development in the field of Quantum Machine Learning. Those bottlenecks are defined by the computation time, energy consumption and quality of obtained results. A wide variety of stakeholders such as computer scientists, machine learning experts, Earth observation experts, agricultural experts, climate scientists, the members of various communities should be involved in identifying mentioned bottlenecks and hard problems related to Earth observations, and later defining the road forward.

It would be advantageous for the research community if several projects were funded. It would allow the gathering of experts from a variety of domains and focus their work on identifying important specific problems in EO that might be solvable using quantum computing and VQAs in particular.

There exists a significant gap between the skills and knowledge of computer scientists of physicists working on quantum computing and practitioners working on e.g. climate change assessment. Therefore, common platforms for scientific discussions have to be organized in order to facilitate communication.

The proposed hybrid machine-learning approach amalgamates an autoencoder for dimensionality reduction of input Earth Observation (EO) images and a quantum algorithm powered by a quantum annealer for mitigating training costs. This innovative methodology capitalizes on the synergies between classical and quantum computing, offering a propitious solution for proficient and accelerated training in Earth Land Cover Understanding. Notably, the independent training capabilities of the two modules facilitate a more adaptive and energy-efficient system.

Considering the potential of this hybrid architecture, it is recommended to investigate hybrid solvers proffered by multiple startups advancing cutting-edge hybrid technology. By establishing collaborations with these startups, researchers and practitioners can gain access to the latest breakthroughs and proficiency in both classical and quantum computing domains. This cooperative endeavor could culminate in the development of more efficacious and efficient hybrid machine-learning models for Earth Land Cover Understanding, ultimately yielding enhanced insights and decision-making capabilities in this field.

As the contemporary landscape of quantum computing continues to evolve rapidly, integrating cutting-edge hybrid technology into Earth Land Cover Understanding can potentially revolutionize the domain. By embracing the strengths of both classical and quantum computing, researchers and practitioners can unlock new possibilities for analyzing and interpreting complex data sets. Ultimately, the pursuit of such hybrid architectures can lead to unprecedented breakthroughs in understanding our planet's land cover, informing crucial decisions related to environmental conservation, climate change, and sustainable development.

We recommend the exploration of hybrid classical-quantum solvers and simulated bifurcation machines for Earth Land Cover Understanding problems. These bleeding-edge technologies offer a unique combination of computational capabilities, which can significantly improve the efficiency and effectiveness of solving complex optimization and classification tasks associated with land cover analysis.

Hybrid classical-quantum solvers, by leveraging the strengths of both classical and quantum computing, can efficiently navigate the solution space and arrive at optimal or near-optimal solutions for Earth Land Cover Understanding problems. Quantum annealers, in particular, can accelerate the training stage by quickly drawing independent samples from the Boltzmann distribution, while classical computing methods can handle the autoencoder and other preprocessing steps. This synergy can reduce the time and energy needed for training, ultimately leading to faster and more accurate results.

Simulated bifurcation machines, on the other hand, provide an alternative approach to quantum annealing that is based on classical computing resources. These machines offer a powerful means to solve combinatorial optimization problems by simulating the bifurcation dynamics of quantum systems, without the need for specialized quantum hardware. As such, simulated bifurcation machines can offer a more accessible and cost-effective solution to Earth Land Cover Understanding problems, while still providing significant performance gains compared to traditional classical computing methods.

In conclusion, adopting hybrid classical-quantum solvers and simulated bifurcation machines for Earth Land Cover Understanding problems can lead to enhanced insights and decision-making capabilities in the field. By exploring these bleeding-edge technologies, researchers and practitioners can unlock new possibilities for analyzing and interpreting complex data sets, ultimately contributing to a better understanding of our planet's land cover and informing critical decisions related to environmental conservation, climate change, and sustainable development.

Quantum computers will likely be only one component of many non-Von Neuman computational accelerators such as e.g. analog, photonic or neuromorphic computers Cavallaro et al. [2022] what makes the landscape of possible non-classical solutions for EO-related problems even more interesting and difficult to navigate in the near future.