Adiabatic and Evolutionary Algorithms for training VQAs

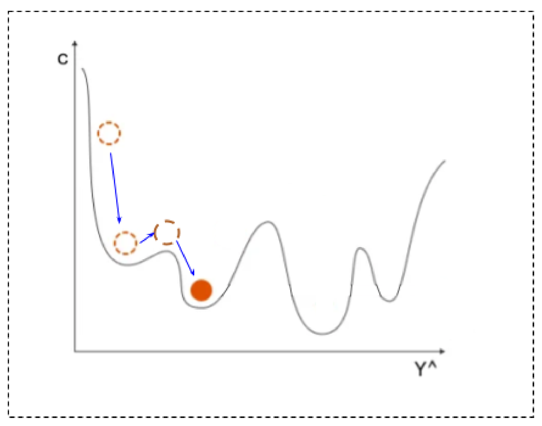
Ernesto Acosta[1] Carlos Cano[1] Guillermo Botella[2]

[1]Universidad de Granada [2]Universidad Complutense de Madrid

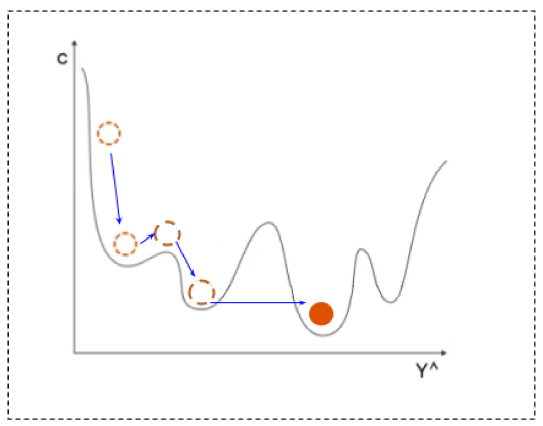
UNIVERSIDAD DE GRANADA

UNIVERSIDAD COMPLUTENSE MADRID

Gradient-free training Variational Quantum Algorithms



Gradient Descent



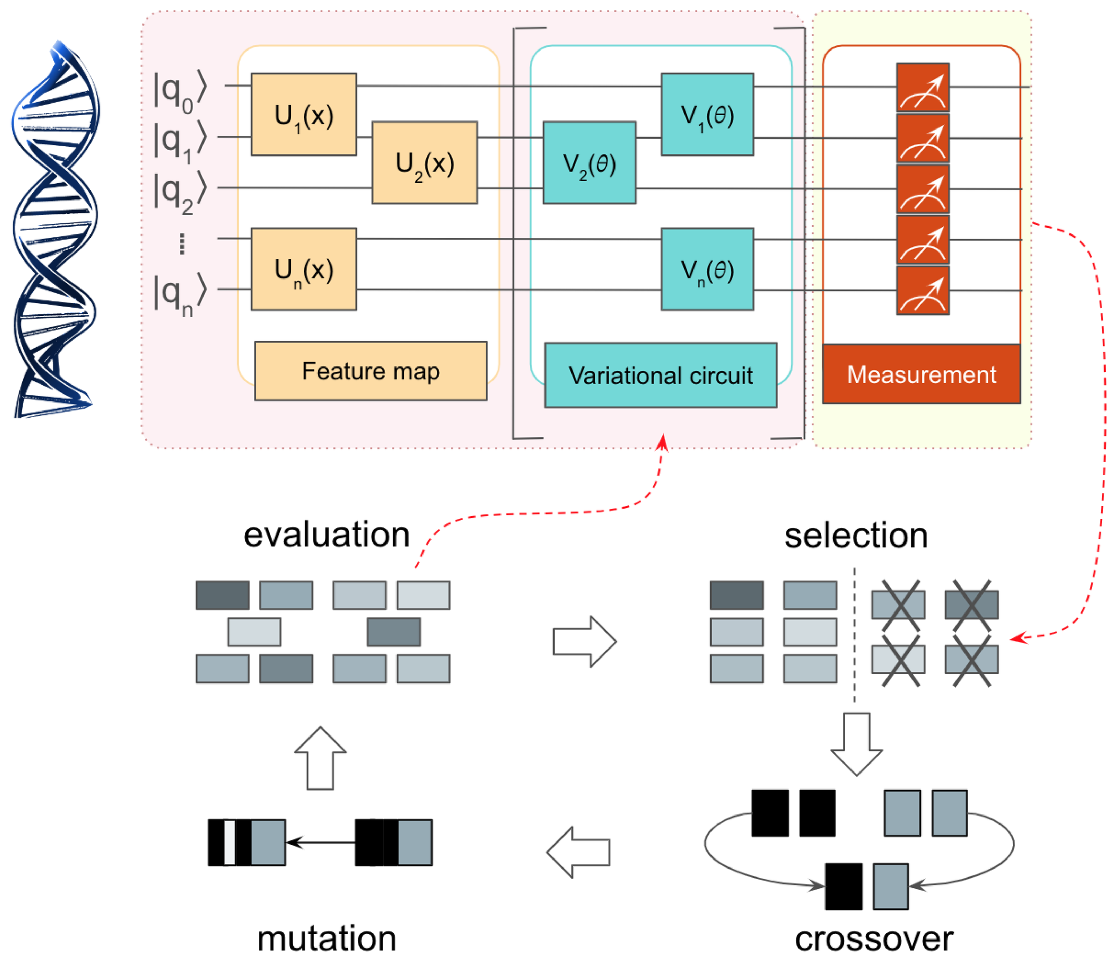
Adiabatic & Evolutionary Training

Evolutionary and Adiabatic Quantum Algorithms are good candidates for training Variational Quantum Algorithms requiring less training iterations to convergence and helping to overcome the barren-plateau effect.
Here we compare these two new approaches.

Evolutionary approach

Evolutionary Training aims to facilitate seamless integration between evolutionary computation and quantum libraries like Qiskit, while ensuring ease of use, for both quantum computing and EAs communities.

Training Process



EVOVAQ Package details

Algorithms included in EVOVAQ framework:

- Genetic Algorithms
- Differential Evolution
- Particle Swarm Optimization
- Memetic Algorithms

Classical optimizer operates by assuming a default value for the hyper-parameters, such as the population size and the stopping criterion.

References

[1] Acampora, G., Cano, C., Chiatto, A., Soto Hidalgo, J.M., Vitiello A.,*EVOVAQ: EVOlutionary algorithms-based toolbox for VAriational Quantum circuits*, SoftwareX, Volume 26, (2024), ISSN 2352-7110 `https://doi.org/10.1016/j.softx.2024.101756`

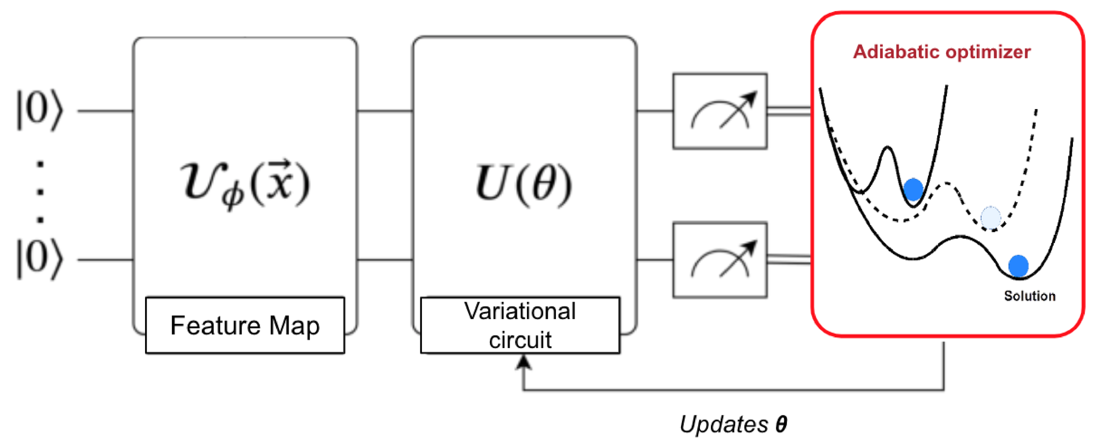
[2] E. Acosta, C. Cano, G. Botella, R. Campos *Adiabatic training for Variational Quantum Algorithms*, EuroQHPC Workshop (2024) `https://doi.org/10.48550/arXiv.2410.18618`

Adiabatic approach

IF: Quantum Annealers are known to be great optimizers

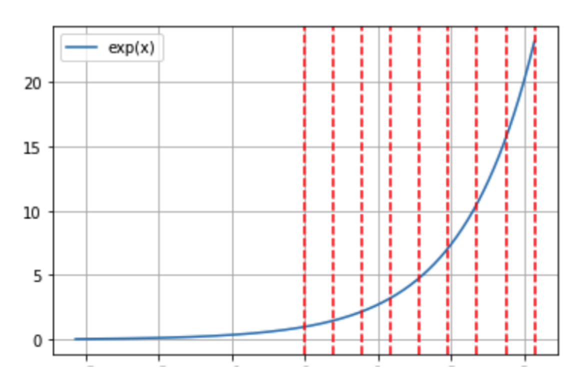
AND: Training VQAs is an optimization task,

THEN: VQAs can be Adiabatically trained by defining a proper QUBO formula.



QUBO Formulation

Angle search range discretization:



x_i	θ	θ/2	exp(θ/2) c_i
x_0	0	0	1
x_1	π/8	π/16	1,216
x_2	π/4	π/8	1,480
x_3	3π/8	3π/16	1,802
x_4	π/2	π/4	2,193
x_5	5π/8	5π/16	2,669
x_6	3π/4	3π/8	3,248
x_7	π	π/2	4,810

Minimization function:

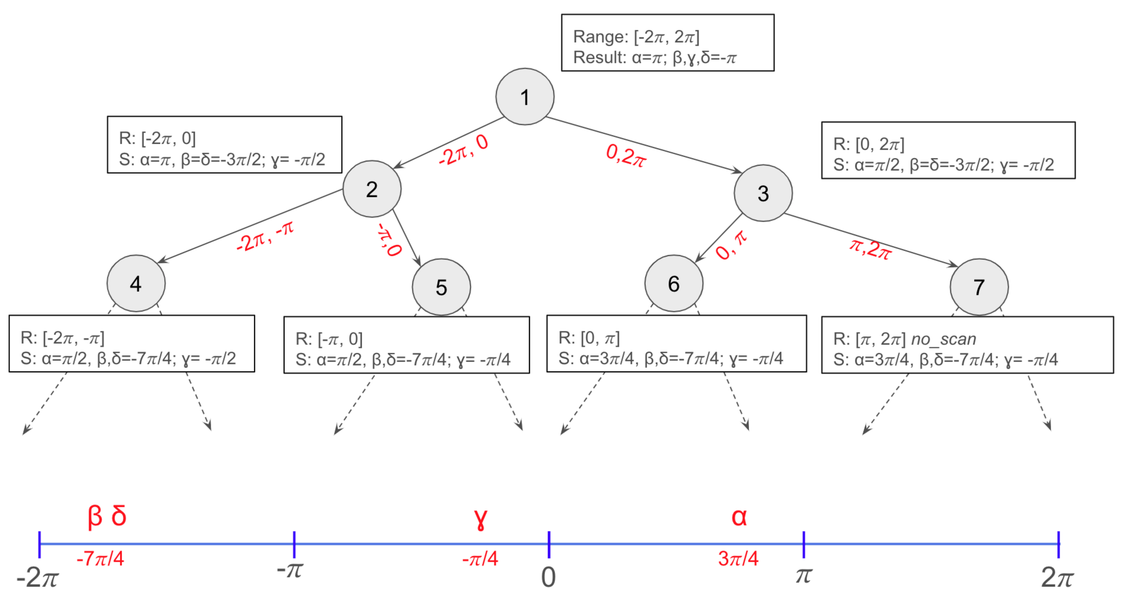
$$\frac{1}{N}\sum_{i=0}^{n-1}\left(\tilde{y}_i(x_i,\vec{\theta})-y_i\right)^2$$

Constraints:

$$\sum_{j=0,k=0}^{(r-1),(p-1)}\theta_i(p)=1$$

Training process

1. Build VQA
2. Discretize angle range in segments.
3. Obtain Ansatz Operator Matrix
4. Prepare QUBO formulation per record:
   - Expand operator
   - Formulate MSE
   - Update global QUBO
5. Run Adiabatic execution
6. Update angles and calc. Accuracy.
7. If accuracy < tolerance, STOP.
8. Repeat step 3 for next segment



Results

	VQA classical	VQA Adiabatic	ANN
Accuracy	66%	66%	64%

Table 1. Accuracies.

Parts	Variables	Options	ANN	Time (s)
3	12	4.096	81	0,926
4	16	65.536	256	0,92
5	20	1.048.576	625	0,927
6	24	16.777.216	1.296	1,13

Table 2. Adiabatic complexity

- Same accuracy with less execution time (ET) and execution cycles (EC).
- EC is constant and ET is smaller for a fixed number of binary variables.
- Iterative approach helps to find the best angles with less resources.
- Adiabatic training is the first hybrid quantum-quantum VQA.

Conclusions

- Accuracy of QRNN with adiabatic training is comparable to classical gradient-descend training on less computing cycles.
- A new research path is presented towards trying to avoid the Barren Plateau effect thanks to the non-gradient dependency.
- The iterative approach overcomes the hardware limitation imposed when trying to optimize in a single scanning step.

Acknowledgements

This work was supported by Ecological and Digital Transition R&D project PID2021-128970OA-I00 call 2022 by MCIN/AEI/10.13039/501100011033 and European Union NextGeneration EU/PRTR, and grant PID2021-123041OB-I00 funded by MCIN/AEI/ 10.13039/501100011033 and by "ERDF A way of making Europe".