Quantum-Assisted Machine Learning in Near-Term Quantum Devices -- Part 2b: QA-based QML

Alejandro Perdomo-Ortiz

Senior Quantum Scientist, Zapata Computing, Canada Honorary Senior Research Associate, Computer Science Dept., UCL, UK

@aperdomoortiz, @ZapataComputing



Funding:



Quantum Languages Designs and Implementation, Sept 28, 2019

Quantum annealing capabilities

2) As a physical device to sample from Boltzmann-like distributions:

$$P_{Boltzman} \propto exp[-\xi(s_1,...,s_N)/T_{eff}]$$

Early work:

Bian et al. 2010. The Ising model: teaching an old problem new tricks.

Follow-up work:

Raymond et al. Global warming: Temperature estimation in annealers. Frontiers in ICT, 3, 23 (2016).

Our work: Benedetti et al. PRA 94, 022308 (2016)

• We provide a robust algorithm to estimate the effective temperature of problem instances in quantum annealers.

 $\langle v_i h_j \rangle_{p(\boldsymbol{h}, \boldsymbol{v})}$

Computationally

bottleneck

Algorithm uses the same samples that will be used for the estimation of the gradient



Potential applications:

- machine leaning (e.g., training of deep-learning networks)

Insight 2: Focus on <u>hybrid</u> quantum-classical approaches. **Cope with hardware constrains and available quantum resources**



Challenges solved:

1. Perdomo-Ortiz, et al. **Opportunities and Challenges** in Quantum-Assisted Machine Learning in Near-term Quantum Computers. <u>Quantum Sci. Tecnol</u>. 3, 030502 (2018).



Challenges of the hybrid approach:

- Need to solve classical-quantum model mismatch

Training Method: Stochastic gradient ascent



No significant progress in 2010-2015 for generative modeling and QA sampling.

Benedetti et al . Phys. Rev. A 94, 022308 (2016)

Resolving model mismatch allows for restarting from classical preprocessing



Benedetti et al . Phys. Rev. A 94, 022308 (2016)

Challenges of the hybrid approach:

 Need to solve classical-quantum model mismatch

Training Method: Stochastic gradient ascent



No significant progress in 2010-2015 for generative modeling and QA sampling.

Benedetti et al . Phys. Rev. A 94, 022308 (2016)

 Robustness to noise, intrinsic control errors, and to deviations from sampling model (e.g., Boltzmann)

Fully visible models



 Curse of limited connectivity – parameter setting
Benede



Benedetti et al. PRX 7, 041052 (2017)

Insight 2: Focus on <u>hybrid</u> quantum-classical approaches. **Cope with hardware constrains and available quantum resources**



Challenges solved:

1. Perdomo-Ortiz, et al. **Opportunities and Challenges** in Quantum-Assisted Machine Learning in Near-term Quantum Computers. <u>Quantum Sci. Tecnol</u>. 3, 030502 (2018).

2. Benedetti, et al. Estimation of effective temperatures in quantum annealers for sampling applications: A case study with possible applications in deep learning. *Phys. Rev. A* 94, 022308 (2016).

3. Benedetti, et al. Quantum-assisted learning of hardware-embedded probabilistic graphical models. <u>Phys. Rev. X</u> 7, 041052 (2017).



OptDigits Datasets

Dataset: Optical Recognition of Handwritten Digits (OptDigits)

OptDigits Datasets



Dataset: Optical Recognition of Handwritten Digits (OptDigits)



42 for pixels + 4 to one-hot encode the class (only digits 1-4)

- Are the results from this training on 940 qubit experiment meaningful?
- Is the model capable of generating digits?

Benedetti, et al. Quantum-assisted learning of hardwareembedded probabilistic graphical models. PRX 7, 041052 (2017)

| 4 4 38 | 31438 | 3 | 38 | 38 | 38 | 38 | | | | | |
|-----------------------------------|----------------------------------|--------------------------------|-----------------------------------|--------------------------------|-----------------------------------|----------------------------------|------------------------------------|-----------------------------------|----------------------------------|--|---------------------|
| 2-28 | 12-28 | 26-28 | 16-28 | 28 | 28 | 38-28 | 28 | 28 | 28 28 | | |
| 30-24 4-20 2 | 15-24 20 31 12-16 | 24 24 3+720 24 26-16 | 43-28 40+20 24 16-16 | 8-28 18¥20 34¥24 13 | 24-28 11,20 24 24 24 | 20-28 23+20 24 38 | 28 20 35-24 | 28 20 24 24 | 28 24/20 20/24 28 | | |
| 30-35 4 223 304 42 2 -30 | 15-35 23 31442 12-15 | 35 3-723 42 26 | 43-35 40 23 42 16 16 | 8-35 1823 34442 13-38 | 33-35 11223 25442 29-38 | 20-35 23 23 42 38 38 | 6-35 42,23 35442 32-38 | 35 35 24 442 38 | 35 35 2423 20042 28-38 | 36-35 4123 27442 21-38 | 2 2 2 |
| 4 18 30 32 2 -13 | 15-8 5 18 311 32 12-13 | 8 3-18 32 26-13 | 43-8 40-18 32 16-13 | 8 8 18 18 34 32 13 13 | 33-28 111718 25932 29-13 | 20-28 23 32 38-13 | 6-28 42 35432 32-13 | 32-28 35 24432 13 | 35-28 24+28 20132 28-13 | 36 41428 27432 21-13 | 17 1 454 |
| 4 /30 30/26 2 -25 | 15-11 5 ¥30 31 26 12-25 | 26-11 3 26 26-25 | 43-11 40 26 16-25 | 8-11 1825 34426 13-25 | 33-11 11/25 25/38 29-25 | 20-23 23,220 23,38 38 | 6 42 | 32 35 24 | 35 24 24 20 28 | 36 41-24 27 21 | 17 1 45 |
| 4 30429 2-14 | 15-33 5 5 31429 12-14 | 26-33 3,5 14429 22-14 | 43-33 4015 29 16-14 | 8-33 18×5 34429 13-14 | 33-33 1115 25429 29-14 | 20-33 31,45 23 38-14 | 6 42-5 10 14 | 32 35-5 24 14 | 35-36 2445 20024 28-14 | 36 36 41 27-24 21 | 17 1 45- |
| 6 4 431 30 2 2 - 4 | 15-6 5 31 31 2 12-4 | 26-6 3 #31 144 3 22 | 43-6 40737 16-43 | 8-6 1837 34411 13-43 | 33-6 11¥37 25411 29-43 | 37-6 37/37 23/11 38-43 | 6 6 42 10 11 11 -43 | 32-6 35+37 11 | 35-6 24431 20011 28-17 | 36-6 41 21 21 21 21 17 | 17 1 25 6 |
| 0 4 - 734 30 - 72 2 - 10 | 15-0 5-34 31422 12-10 | 26-0 3 34 14422 22-10 | 43-0 40734 22022 16-10 | 8-0 18734 34422 13-10 | 33-0 11 25422 29-10 | 37-0 0,¥38 236,22 38-10 | 6-0 42239 10922 11-10 | 32-0 35¥39 39¥22 10-10 | 35-0 24420 20022 28-10 | 36 41-20 27 21-10 | 17 1 45 6 |
| 4)-44 4)19 302 9 2-7 | 15-44 5 19 314 9 12-7 | 26-44 3 19 144 9 7 7 | 43-44 4019 2229 16-7 | 8-44 18,19 34,9 13-7 | 33-44 11119 2529 29-7 | 37-44 0×19 2349 38-7 | 9-44 42,19 1949 21-7 | 32-44 19 392 9 10-7 | 35-44 24419 2049 28-7 | 36-44 41 27 21-7 | 17-1 45 |
| 41-39 4 21 30 36 2 - 3 | 15-39 5 27 31236 12-3 | 26-39 3 27 14.136 3 | 43-39 4027 22236 16 | 8-39 1827 34436 13 | 33-39 27 25436 29 | 37-39 01/27 39936 36-17 | 9-39 2727 19506 21-17 | 32-39 17.227 39736 36-17 | 39 24-27 36 39 | 36 41-27 27/36 21 | 17 1 45 19 |
| 41-21 4 30440 2-41 | 15-21 5-12 311,40 12-41 | 26-21 3416 14440 41 | 43-21 40716 228,40 16-41 | 8-21 18 34 21-41 | 33-21 33/33 25 29-41 | 45-21 0 0 39 41 41 | 9-21 27-41 19 41 41 | 21 21 17-41 21 36 | 41 21 | 41 41 21 21 | 17 1 45 19 |
| 45 30443 2-17 | 15-45 5 1 31443 12-17 | 26-45 3 21 14443 17 | 43-45 40,1 222443 16-17 | 8-45 18-1 34 | 45 33/1 25 29-17 | 45 45 1 11 39 41-17 | 9-45 27+1 19 19 17 | 45 17-1 19 36-17 | 45 1 19 17 | 45 1 19 17 | 17 1 254 |

Human or (quantum) machine? (Turing test)



Dataset: Optical Recognition of Handwritten Digits (OptDigits)

Results from experiments using 940 qubits, without post-processing. The hardware-embedded model represents a 46 node fully connected graph.

Benedetti, et al. PRX 7, 041052 (2017)

Human or (quantum) machine? (Turing test)



Dataset: Optical Recognition of Handwritten Digits (OptDigits)

Results from experiments using 940 qubits, without post-processing. The hardware-embedded model represents a 46 node fully connected graph.

Benedetti, et al. PRX 7, 041052 (2017)

Challenges of the hybrid approach:

- Need to solve classical-quantum model mismatch

Training Method: Stochastic gradient ascent



No progress in five years since QA sampling was proposed as a promissing appplication. Robustness to noise, Ful intrinsic control errors, and to deviations from sampling model (e.g., Boltzmann)





Visible units

 Curse of limited connectivity – parameter setting

Benedetti et al. arXiv:1609.02542

How about large complex datasets with continuous variables? All previous fail to do that (fully quantum and hybrid here)

Insight 2: Focus on <u>hybrid</u> quantum-classical approaches. **Cope with hardware constrains and available quantum resources**



Challenges solved:

1. Perdomo-Ortiz, et al. **Opportunities and Challenges** in Quantum-Assisted Machine Learning in Near-term Quantum Computers. <u>Quantum Sci. Tecnol</u>. 3, 030502 (2018).

2. Benedetti, et al. Estimation of effective temperatures in quantum annealers for sampling applications: A case study with possible applications in deep learning. *Phys. Rev. A* 94, 022308 (2016).

3. Benedetti, et al. Quantum-assisted learning of hardware-embedded probabilistic graphical models. *Phys. Rev. X 7, 041052 (2017).*

4. Benedetti, et al. Quantum-assisted Helmholtz machines: A quantum-classical deep learning framework for industrial datasets in near-term devices.

<u>Quantum Sci. Technol</u>. 3, 034007 (2018).

Perspective on quantum-enhanced machine learning

• New hybrid proposal that works directly on a low-dimensional representation of the data.



Perspective on quantum-enhanced machine learning

• New hybrid proposal that works directly on a low-dimensional representation of the data.



Perspective on quantum-enhanced machine learning

• New hybrid proposal that works directly on a low-dimensional representation of the data.



Experimental implementation of the QAHM



Experiments using 1644 qubits (no further postprocessing!)

Max. CL = 43

Acknowledgments

Institutions/ Funding





Theory collaborators

M. Benedetti (UCL), J. Realpe-Gomez(NASA), R. Biswas (NASA).

alejandro@zapatacomputing.com, @aperdomoortiz, @ZapataComputing