THE AFRL-USRA-NYSTEC QUANTUM INFORMATION SCIENCE PROGRAM

Davide Venturelli, Ph.D.
USRA Quantum Computing Science Lead

and Research Scientist @ Quantum AI Laboratory (QuAIL)
– NASA Ames Research Center (NASA Academic Mission Service Contract)

dventurelli@usra.edu
AFRL-USRA-NYSTEC QIS PROGRAM

Here at the workshop:

Evan DeGennaro  Bernie Seery
USRA AND NASA EFFORTS ON QUANTUM COMPUTING

USRA is a non-profit that was created in 1969 by the National Academy of Sciences

The USRA Research Institute for Advanced Computer Science (RIACS) was created in 1983 in collaboration with NASA’s Ames Research Center

RIACS Research Includes
• Quantum Computing
• Artificial Intelligence
  • Machine Learning
  • Autonomous Systems
• Bioinformatics
• Nanotechnology

http://www.usra.edu/quantum/
https://ti.arc.nasa.gov/tech/dash/groups/physics/quail
TALK OUTLINE

- Short introduction to Quantum Computing
- Near-term Quantum Computing: Quantum Annealing and Quantum Approximate Optimization
- QIS Program Lectures and Website
- QIS Program Newsletter
- QIS Program R&D (Feynman Quantum Academy)
FAST RECAP ON QUANTUM COMPUTING: QUBITS

Bit
0

Qubit
0

1

Very small

Very protected

Very cold

= QM
FAST RECAP ON QUANTUM COMPUTING: QUBITS
RSA-2048: 2048 bit number (617 digits)
10 years all USA
millions of trillions of $
World energy 1 day

7 hours in a quantum computer.

23 million qubits for error-correction

BUYER BEWARE
(\pi/4) \sqrt{N}

1000 queries → \approx 30 queries

Applicable to almost any combinatorial search problem. (A. Montanaro)

Additional proof of unbeatable power of quantum computing

QUANTUM «DATA SEARCH» : GROVER ALGORITHM
Recent studies show that for problems that require less than 1 day, in superconducting qubits chip it would not be viable, due to overhead.
QUANTUM «LINEAR SYSTEM SOLVER» (HHL)

Classical: $N^2$

Quantum: $\log(N)$

$100^2 = 10,000$

$\ln(100) \approx 5$

- Longest term algorithm known.
- Real time rendering of immense data.
- Applications in finance, big data.
- Can accelerate machine learning.
Only a small number of quantum algorithms known with established quantum advantage... Not surprising at this early stage of quantum information processing hardware!

How broad will the applications of quantum computing ultimately be?

What are the chances that the only compelling speedup we can get out of QC is the one we can prove ab-initio?

\[ 2^N \rightarrow \alpha 2^{\beta N^\gamma} \]

\( \alpha \) “quantum-asic”

\( \beta \) expectations from grover

\( \gamma \) ???

Davide Venturelli – July 10, 2019 - Utica – dventurelli@usra.edu
Quantum Annealers

Superconducting Gate-Model NISQs QPUs

Other Post-Moore Approaches

≈2000

≈70(?)

≈20

≈50(?)

≈16(?)

≈1000

≈50(?)

≈50(?)

≈1000
From 2013, USRA is providing free competitive access to use of the D-Wave 2000Q machine.
# QUANTUM ANNEALING - STATUS

**The D-Wave machine at NASA Ames**

<table>
<thead>
<tr>
<th>D-Wave Two™</th>
<th>D-Wave 2X™</th>
<th>D-Wave 2000Q™</th>
</tr>
</thead>
<tbody>
<tr>
<td>512 (8x8x8) qubits “Vesuvius”</td>
<td>1152 (8x12x12) qubit “Washington”</td>
<td>2048 (8x16x16) qubit “Whistler”</td>
</tr>
<tr>
<td>1152 qubits working – 95% yield</td>
<td>1097 qubits working – 95% yield</td>
<td>2038 qubits working – 97% yield</td>
</tr>
<tr>
<td>1472 ( J ) programmable couplers</td>
<td>3360 ( J ) programmable couplers</td>
<td>6016 ( J ) programmable couplers</td>
</tr>
<tr>
<td>20 mK max operating temperature (18 mK nominal)</td>
<td>15 mK Max operating temperature (13 mK nominal)</td>
<td>15 mK Max operating temperature (nominal to be measured)</td>
</tr>
<tr>
<td>5% and 3.5% precision level for ( h ) and ( J )</td>
<td>3.5% and 2% precision level for ( h ) and ( J )</td>
<td>To be measured.</td>
</tr>
<tr>
<td>Annealing time 20 ( \mu s )</td>
<td>Annealing time improved 4x (5( \mu s ))</td>
<td>Annealing time improved 5x (1( \mu s ))</td>
</tr>
<tr>
<td>Readout time improved (120( \mu s ))</td>
<td>Initial programming time improved 20% (9 ms). Extented J, anneal offset, pause and quench features. (+h field schedules [2019])</td>
<td></td>
</tr>
</tbody>
</table>
APPLICATIONS TESTED SO FAR
• Every generation \(20x+\) improvement!
• Already available low-noise chip \((25x+)\)
• New upgrade in architecture should have at least a factor of 3 in increased embeddability of fully-connected graphs, and 5000 qubits for a total of \(N = 180 \times 2 = 360\)

**Anticipated 100x+ improvement!**

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<td>Max degree</td>
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<td>60</td>
<td>180</td>
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### Couplers Native CZ

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<td>1-7</td>
<td>179 ns</td>
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<td>2-7</td>
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<td>2-8</td>
<td>189 ns</td>
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<td>4-9</td>
<td>122 ns</td>
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<td>5-10</td>
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<td>6-11</td>
<td>180 ns</td>
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<td>8-13</td>
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<td>9-14</td>
<td>139 ns</td>
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<td>142 ns</td>
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### Couplers Native CX

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<td>283 ns</td>
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<td>15-0</td>
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<tr>
<td>15-2</td>
<td>391 ns</td>
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<tr>
<td>15-14</td>
<td>183 ns</td>
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A Quantum Approximate Optimization Algorithm

Edward Farhi and Jeffrey Goldstone
Center for Theoretical Physics
Massachusetts Institute of Technology
Cambridge, MA 02139

Sam Gutmann

Abstract

We introduce a quantum algorithm that produces approximate solutions for combinatorial optimization problems. The algorithm depends on an integer $p \geq 1$ and the quality of the approximation improves as $p$ is increased. The quantum circuit that implements the algorithm consists of unitary gates whose locality is at most the locality of the objective function whose optimum is sought. The depth of the circuit grows linearly with $p$ times (at worst) the number of constraints. If $p$ is fixed, that is, independent of the input size, the algorithm makes use of efficient classical pre-processing. If $p$ grows with the input size a different strategy is proposed. We study the algorithm as applied to MaxCut on regular graphs and analyze its performance on 2-regular and 3-regular graphs for fixed $p$. For $p = 1$, on 3-regular graphs the quantum algorithm always finds a cut that is at least 0.0024 times the size of the optimal cut.
Bitflip mixers
• Maximum Cut
• Max-SAT, Min-SAT, NAE-SAT
• Set Splitting
• MaxE3LIN2

Controlled Bitflip mixers
• MaxIndependentSet
• MaxClique
• MinVertexCover
• MaxSetPacking
• MinSetCover

XY mixers
• Max-ColorableSubgraph
• Graph Partitioning
• Maximum Bisection
• Max Vertex k-Cover

Controlled XY mixers
• Max-k-ColorableInducedSubgraph
• MinGraphColoring
• MinCliqueCover

Applications

DARPA Defense Advanced Research Projects Agency > News And Events
Taking the Next Step in Quantum Information Processing
DARPA to leverage intermediate-sized quantum devices to help solve complex optimization problems
OUTREACH@DARPA.WIL
2/27/2019

From the Quantum Approximate Optimization Algorithm to a Quantum Alternating Operator Ansatz

Stuart Hadfield*, Zihui Wang†,‡, Bryan O’Gorman†,‡, Eleanor G. Rieffel†, Davide Venturelli*,‡, Rupak Biswas†

* Department of Computer Science, Columbia University, New York, NY
† Quantum Artificial Intelligence Lab., NASA Ames Research Center, Moffett Field, CA
‡ USRA Research Institute for Advanced Computer Science (RIACS), Mountain View, CA
§ Singer Quantian Technologies, Inc., Greenbelt, MD
¶ Berkeley Quantum Information and Computation Center and Departments of Chemistry and Computer Science, University of California, Berkeley, CA

September 12, 2017

The next few years will be exciting as prototype universal quantum processes emerge, enabling implementation of a wider variety of algorithms. Of particular interest are quantum heuristics, which require experimentation on quantum hardware for their evaluation, and which have the potential to significantly expand the breadth of applications for which quantum computers have an established advantage. A leading candidate is Farhi et al.’s Quantum Approximate Optimization Algorithm, which alternates between applying a cost-function-based Hamiltonian and a mixing Hamiltonian. Here, we extend this framework to allow alternation between more general families of operators. The essence of this extension, the Quantum Alternating Operator Ansatz, is the consideration of general parameterized families of unitaries rather than only those corresponding to the time-evolution under a fixed local Hamiltonian for a time specified by the parameter. This ansatz supports the representation of a larger, and potentially more useful, set of states than the original formulation, with potential long-term impact on a broad array of application areas.
APPLICATIONS CONCEIVED SO FAR

Bitflip mixers
- Maximum Cut
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Controlled Bitflip mixers
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XY mixers
- Max-ColorableSubgraph
- Graph Partitioning
- Maximum Bisection
- Max Vertex k-Cover

Controlled XY mixers
- Max-k-ColorableInducedSubgraph
- MinGraphColoring
- MinCliqueCover

Permutation mixers
- TSP
- SMS with various metrics and constraints

From the Quantum Approximate Optimization Algorithm to a Quantum Alternating Operator Ansatz


* Department of Computer Science, Columbia University, New York, NY
† Quantum Artificial Intelligence Lab., NASA Ames Research Center, Moffett Field, CA
‡ USRA Research Institute for Advanced Computer Science (RIACS), Mountain View, CA
§ Stringer Griffinian Technologies, Inc., Greenbelt, MD

September 12, 2017

The next few years will be an exciting time for quantum computing as new and imaginative processors emerge, enabling increased levels of scalability. One particular interest of the Quantum Artificial Intelligence Laboratory is the Quantum Approximate Optimization Algorithm (QAOA). We have an established advantage on the current QAOA hardware, which is based on a Hamiltonian circuit model. The essence of this extension, the quantum alternating operator ansatz, is the consideration of general parameterized Hamiltonians, including those corresponding to the time-evolution under a fixed local Hamiltonian for a time specified by the parameter. This ansatz supports the representation of a larger, and potentially more useful, set of states than the original formulation, with potential long-term impact on a broad array of application areas.
THE IMPORTANCE OF A QUALIFIED WORKFORCE

True understanding comes from getting the hands dirty and trying to make an impact in applied near-term QC
ACTION 1: QIS PROGRAM LECTURES AND SEMINARS

- Edited videos
- Download material
- Reference Publications

Note: Images and lecture topic shown are examples
ACTION 1: QIS PROGRAM LECTURES AND SEMINARS

Note: Images and lecture topic shown are examples

1) INTRODUCTION ON QAOA
(30min video, slides, downloadable references)

2) EXERCISE ON QAOA PARAMETER SETTING
(20min video, solution notes)

3) LECTURE ON QAOA ANSATZ DESIGN
(30min video, slides)

4) EXERCISE, CODING GRAPH COLORING
(20min video, slides, jupyter notebook)

5) RESEARCH SEMINAR ON XY-MIXERS
(45min, downloadable paper and references)

- Edited videos
- Download material
- Reference
- Publications
Categories

**NISQ Algorithms:**
- Optimization
- Machine Learning
- Simulation
- Software and Benchmarking

**QC-Inspired NISQ Experiments:**
- Superconducting
- Optics
- Atoms
- Analog
- Other Digital
- QC-Inspired

*Soon interactive!*
ACTION 2: QIS PROGRAM NEWSLETTER

NISQC COMPUTING NEWSLETTER

The RIACS NISQ Computing Newsletter is a monthly curated digest of the latest preprints that are impacting the field of near-term quantum computing. We feature exclusively experiments that advance the field of applied quantum computing in existing hardware, or theoreatically-experiments tightly connected to experimental realization in the near term.

Anyone can submit paper notifications to be considered in the newsletter.

Recent Newsletters
NISQC-NL #2 – May 16-June 15
NISQC-NL #1 – April 16-May 15

Categories

<table>
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<tr>
<th>NISQ- NL #1</th>
<th>NISQC-NL #2</th>
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<tr>
<td>NISQ Algorithms:</td>
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Soon interactive!

https://riacs.usra.edu/quantum/NISQC-NL
Ph.D or Strong Undergrad with previous research experience
Applications open for Winter period (November-March)

Davide Venturelli – July 10, 2019 - Utica – dventurelli@usra.edu
ACTION 3: QIS PROGRAM R&D AND QUANTUM ACADEMY

2017
S. Hadfield (Columbia→USRA) ⭐
D. Roberts (Harvard→UChicago) ⭐⭐
M. Adnane (ENS→UCB) ⭐⭐*

2018
B. Villalonga-Correa (UIUC→Google) ⭐
S. Nanda (Caltech) ⭐*
R. Mengoni (univ. Verona) ⭐
A. Bapat (UMD) ⭐
J. Marshall (USC→USRA) ⭐
A. DiGioacchino (univ. Milan) ⭐⭐
K. Booth (Utoronto→USRA) ⭐

2019 (excluding the students supported by this program)
- M. Kim (Princeton) – *quantum annealing and CIM benchmark in Wireless Network Decoding problems*
- Zoe Gonzalez Izquierdo (USC) - Quantum annealing approaches to graph connectivity problems
- Lindsay Bassam (USC) - *Resource and performance estimates for material science applications of quantum computing*
- T. Parolini (SISSA, Triest) – *Study of Many-Body Delocalization for quantum annealing speedup*
- Vladimir Kremenetski (UCB) - *adiabatic evolution/state preparation using arbitrary wave functions and geodesic construction of short quantum circuits*
- Sathyawageeswar Subramanian (Cambridge) – *Variational quantum algorithms*
- Andrea Skolik
- Michael ...

⭐ Peer-reviewed publication
⭐⭐ Conference Talk / Poster
⭐⭐⭐ Pre-print in preparation

* Undergrad
ACTION 3: QIS PROGRAM R&D AND QUANTUM ACADEMY

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From the Quantum Approximate Optimization Algorithm to a Quantum Alternating Operator Ansatz

Stuart Hadfield*, Zhihui Wang*,*, Bryan O’Gorman*,*,*,*, Rupak Biswas*,
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* Department of Computer Science, Columbia University, New York, NY
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Shorter Gharibian Technologies, Inc., Greenbelt, MD
1 Berkeley Quantum Information and Computation Center and Departments of Chemistry and Computer Science, University of California, Berkeley, CA

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Peer-reviewed publication
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ACTION 3: QIS PROGRAM R&D AND QUANTUM ACADEMY

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A. Bapat (UMD) *
J. Marshall (USC → USRA)
A. DiGioacchino (univ. Milan)
K. Booth (Utoronto → USRA)

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A flexible high-performance simulator for the verification and benchmarking of quantum circuits implemented on real hardware

Benjamin Villalonga, 1,2,3,4 Sergio Boixo, 5,6,7 Iordanis Kerenidis, 2,4,7,8 Ronald de Queiroz, 2,4,7,9 Christopher Nemeth, 3,4,7,9 Xingfeng Zeng, 2,4,7,9

1 Immanuel Machine Learning Lab, IBM Research, Yorktown Heights, NY, USA
2 IBM Research - Almaden, San Jose, CA, USA
3 IBM Research - T.J. Watson Research Center, Yorktown Heights, NY, USA
4 IBM Research - Zurich, Zurich, Switzerland
5 IBM Cross-Functional Research (CQR), Yorktown Heights, NY, USA
6 IBM Research - Duke, Durham, NC, USA
7 IBM Quantum, IBM
8 IBM Quantum, IBM Research – Tokyo, Japan
9 IBM Quantum, IBM Research – Austin, Austin, TX, USA

2017
Matthew Adnane (ENS → UCB) *

2018
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A. Bapat (UMD) *
J. Marshall (USC → USRA)
A. DiGioacchino (univ. Milan)
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Peer-reviewed publication
Conference Talk / Poster
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The new benchmark quantum computers must beat to achieve quantum supremacy

Physicists are confident that a quantum computer will soon outperform the world’s most powerful supercomputer. To prove it, they have developed a test that will pit one against the other.
### ACTION 3: QIS PROGRAM R&D AND QUANTUM ACADEMY

#### 2017
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- J. Marshall (USC → USRA)
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<th>Year</th>
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**Peer-reviewed publication**

**Conference Talk / Poster**

**Pre-print in preparation**

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ACTION 3: QIS PROGRAM R&D AND QUANTUM ACADEMY

**R&D «Hot» Theme: optimization of quantum programs**

D. Bernal (CMU) – *algebraic geometric methods to embed problems in pegasus annealer and route qubit information in NISQ compilers*

R. LaRose (MSU) – starting in September – *End-to-End Software Architecture and benchmarking of compilation of quantum circuit*

[we have space for other students/visiting researchers, apply!]

https://riacs.usra.edu/quantum/QAcademy

Assign “colors” to connected sets of qubits

\[ \mathcal{E}(i) : \{1, \ldots, n_L\} \to 2^{\{1, \ldots, n_P\}} \]

\( n_H \) hardware qubits
**ACTION 3: QIS PROGRAM R&D AND QUANTUM ACADEMY**

**R&D «Hot» Theme : optimization of quantum programs**

D. Bernal (CMU) – algebraic geometric methods to embed problems in pegasus annealer and route qubit information in NISQ compilers

\[ \alpha_{ij} \in \{0,1\} \text{ (logical qubit } j \text{ is assigned to physical qubit } i) \]
\[ \beta_i \in \{0,1\} \text{ (physical qubit } i \text{ is used}) \]

\[ \pi(x) = \sum_{j \in \psi : x_j \in V(X)} a_{ij} \]
\[ \sum_{j \in \psi : x_j \in V(X)} a_{ij} = \beta_i \]
\[ a_{ij} \in \{0,\forall j : j \neq j, (y_j, y_j) \in V(Y) \} \]
\[ a_j (a_j - 1) = 0, \forall y_j : y_j \in V(Y) \]
\[ \beta_i (\beta_i - 1) = 0 \]
\[ \sum_{x_i \in \psi : x_j \in V(X)} a_{ij} \leq k \Rightarrow \prod_{j=1}^{k} \left( \sum_{x_i \in \psi : x_j \in V(X)} a_{ij} - k \right) = 0 \]
\[ \prod_{j=1}^{k} \left( \sum_{x_i \in \psi : x_j \in V(X)} a_{ij} - k \right) = 0 \]
\[ a_{ij} = 0, \forall y_j : y_j \in V(Y) \]

\[ a_{ij} \geq k \Rightarrow \prod_{j=1}^{k} \left( \sum_{x_i \in \psi : x_j \in V(X)} a_{ij} - k \right) = 0 \]
\[ \prod_{j=1}^{k} \left( \sum_{x_i \in \psi : x_j \in V(X)} a_{ij} - k \right) = 0 \]

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Assign “colors” to connected sets of qubits
\[ E(i) : \{1, \ldots, n_L\} \to 2^{\{1, \ldots, n_P\}} \]

(n_p logical bits)

(n_h hardware qubits)
QUESTIONS?

https://riacs.usra.edu/quantum/

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