الگوریتمهای کوانتومی وردشی مروری بر پیشرفتها و چالشها

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Contents

What are VQAs?
Applications
Challenges
Solutions



Machine Learning, a bit of history

- 1943: Artificial Neuron Input Signal > Threshold -> Output
- Activation function
 - ReLU (Rectified Linear Unit)







Machine Learning, neural networks





Is this a Cat?



Variational Quantum Algorithms





 We have a parameterized quantum circuit!

 Training means finding the right set of parameters

 U_1 (



VQA: Cost function

Cost function: – The circuit U(heta)- States from a training set $\{\rho_k\}$ -A set of Observables $\{O_k\}$ $C(ec{ heta}) = \sum f_k \left({
m Tr} \left[O_k U(ec{ heta})
ho_k U^\dagger(ec{ heta})
ight]
ight)$



VQA: Ansatz

It's the form of circuit we pick

Ansatz Expressibility

Compare states with Haar random

Entangling Capability

....

Problem inspire

Variational Hamiltonian

Problem agnostic

HEA

....

QAOA

UCC

Variable structure

ADAPT-VQE Mog-VQE

Hybrid

Types

Ansatz

Sub-logical

VQA: Training



Gradient descent

Optimization

Gradient-free methods



Parameter Shift rule

Gradients





https://www.nature.com/articles/s42254-021-00348-9



Generative Models

Quantum Chemistry

Condensed Matter

Ex. 1: Variational Quantum Eigensolver

- Cost function $C(\vec{ heta}) = \langle \psi(\vec{ heta}) | H | \psi(\vec{ heta})
angle , \ |\psi(\vec{ heta})
angle = U(\vec{ heta}) | \psi_0
angle$

 The Hamiltonian usually has the form:

$$H = \sum_{k} c_k \sigma_k$$

https://www.nature.com/articles/s41586-019-1040



Ex. 2 Dynamical Quantum Simulation

Increase fidelity between: $\exp(-iH\delta t)\,, U(ec{ heta}^*)\mathcal{T}(E,\delta t)U^\dagger(ec{ heta}^*)$

ariational Fast Forwarding

Dynamical Quantum Simulation

Simulating Open Systems

 $\left\| \min_{ec{\delta}} \delta \, \left\| \left(rac{d}{dt} + i H
ight) \left| \psi(ec{ heta})
ight
angle
ight
angle$ $\Rightarrow M(ec{ heta}). \, \dot{ec{ heta}} = V(ec{ heta})$ $ec{ heta}
ightarrow ec{ heta}
ightarrow ec{ heta}
ightarrow \Delta t$ Iterative Approac Subspace Approact Map the state to comp. basis. $\exp(-iHt)pprox U(ec{ heta}^*)\mathcal{T}(t)U^\dagger(ec{ heta}^*)$

Ex. 3: Optimization, e.g. QAOA

 Map a classical optimization problem to a Hamiltonian:

 $C(z) = \sum_{lpha=1}^m C_lpha(z)$



• A mixer operator $B = \sum_{j=1}^{n} \sigma_{j}^{X}$ • Optimize angles $\vec{\beta}, \vec{\gamma}$

Doubts: Overview

Getting stuck in local minima

Challenges

gradients)

Are there any improvements?

Barren Plateaus (Vanishing

Local minima

- There is evidence that the parameter hyperspace is not smooth!
 - "Beyond Barren Plateaus: Quantum Variational Algorithms Are Swamped With Traps", 2022
 - "Training Variational Quantum Algorithms Is NP-Hard", 2021

arXiv:2101.07267v1, arXiv:2205.05786v1



Barren Plateau

In many cases it has been proven that the gradients will be exponentially small.

Barren Plateau

Noise induced

Excess expressivity

Global cost function

Entanglement

Barren Plateau: Expressiveness

We know:

 $C(ec{ heta}) = \mathbf{Tr} \Big[HU(ec{ heta})
ho U(ec{ heta})^{\dagger} \Big]$ $Pigg(rac{\partial C}{\partial heta_k} \geq \deltaigg) \leq rac{\mathbf{Var}(\partial_k C)}{\delta^2}$

 As the expressibility of the circuit grows, the variance becomes exponentially smaller!

DOI: 10.1103/PRXQuantum.3.010313





Barren Plateau: Noise Induced

- Noise: Expectation value of an operators -> its average
- Flattens the parameter space
- E.g. QAOA for MaxCut

DOI: 10.1038/s41467-021-27045-6



Barren Plateau: Global cost function

 Circuit depth as well as global cost function can cause BP.



DOI: 10.1038/s41467-018-07090-4 DOI: 10.1038/s41467-021-21728-w



Circuit

Depth

Our

Work:

Barren Plateau: Entanglement



DOI: 10.1007/s42484-023-00103-6 DOI: 10.1103/PhysRevLett.128.180505 DOI: 10.1103/PRXQuantum.2.040316

Solutions



Solutions: Noise



NISQ-era VQA challenges!

Solutions: LM -> Overparametrization

- Overparametrization can increase the success probability.
- The rank of the Quantum **Fisher Information Matrix is a** good threshold.
- Noise can affect these in a non-intuitive manner.
 - Increases the rank of QFIM
 - Eigs. exponentially small, insensitive to change



DOI: 10.1038/s43588-023-00467-6 https://arxiv.org/abs/2302.05059v1

Solutions: BP -> Careful design

It is very important to choose a good ansatz.

- Some ansatz do not exhibit Barren plateaus.
- There are also techniques one can use in the design of the ansatz to avoid barren plateaus.



DOI: 10.1103/PhysRevX.11.041011 DOI: 10.1103/PRXQuantum.3.020365

Solutions: BP -> Hot start

- There are proposals to use techniques such as:
 - Classical machine learning
 - MPS

....

- Classical Shadows
- Start from:
 - Good initial states.
 - Good set of parameters
- Avoid the BP region.

DOI: 10.1088/1367-2630/acb58e, DOI: 10.1103/PRXQuantum.3.020365





Promising Possible Applications

Chemistry and material science

Molecular structure

- Molecular dynamics

- Material science

Opportunities

Particle Physics

Nuclear Physics

Nuclear and Particle Physics

Optimization and Machine Learning

Optimization

Machine Learning

See doi: 10.1038/s42254-021-00348-9 and references therein.

Summary

 Variational Quantum Algorithm is a promising approach for getting quantum improvements in NISQ-era.

 There are certain pitfalls one should avoid. Its true power is likely to become apparent as more powerful quantum computers emerge.

Thank you!

